Climate change in news media across the globe: an automated analysis of issue attention and themes in climate change coverage in 10 countries (2006–2018)

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Abstract: Climate change poses a challenge to countries across the world, with news media being an important source of information on the issue. To understand how and how much news media cover climate change, this study compares coverage in ten countries from the Global North and the Global South between 2006 and 2018 (N = 71,674). Based on a panel analysis, we illustrate that news media attention varies across countries and is often associated with political, scientific, and (partly) societal focusing events. Based on an automated content analysis, we also find that news media do not only cover ecological changes or climate science, but that they focus predominantly on the societal dimension of climate change: They emphasize how humans are aware of, affected by, battle, or cause climate change. Overall, the study illustrates important differences between the Global North and the Global South. While countries from the Global North cover climate change more frequently, countries from the Global South focus more on its challenges and implications for society at large, i.e., the societal dimension of climate change.

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Supplementary Material

Table of Content

Tables and Figures

Appendix A. Corpus Construction & Data Cleaning

Our corpus consists of newspaper articles discussing climate change as their main topic in ten countries from the Global North and the Global South between 2006 and 2018.

A1. Corpus Construction

As legacy media have been shown to amplify public attention (Langer and Gruber, 2020), we sampled articles from two leading, widely circulating national quality newspapers for each country. Our sample includes the following countries and newspapers for the Global North: Australia (*The Australian*, *Sydney Morning Herald*), Canada (*Globe & Mail*, *Toronto Star*), Germany (*Süddeutsche Zeitung, Frankfurter Allgemeine Zeitung*), New Zealand (*NZ Herald*, *The Press*), the UK (*The Guardian*, *The Times*), and the US (*The New York Times*, *The Washington Post*). For the Global South, the following countries and newspapers were included: India (*Hindu*, *Times of India*), Namibia (*Allgemeine Zeitung*, *The Namibian*), South Africa (*Sunday Times*, *The Star*), and Thailand (*Bangkok Post*, *The Nation*). Across all ten countries, news between 2006 and 2018 featuring the following search terms at least twice were retrieved:

"climate change OR global warming* OR greenhouse effect*"* (English language outlets)

"Klimawandel OR (global* AND Erwärmung*) OR Treibhauseffekt*"* (German language outlets)

German language articles were translated to English via the Google Translate API, an approach that has been shown to deliver robust results in the context of climate change coverage (Reber, 2019) and beyond (de Vries et al., 2018; Lucas et al., 2015; Windsor et al., 2019).

A2. Data Cleaning

Next, we dealt with potential noise in our data. Grundmann (2021) argues that computational analyses often introduce noise during corpus construction, for example by not eliminating duplicate or irrelevant texts. To reassure that this was not the case for our analysis, we describe important steps related to data cleaning in more detail here: (1) the removal of duplicates and (2) the removal of irrelevant content.

Removal of Duplicates. A common problem when retrieving data from web archives is that these may include duplicates, for example texts that only differ by a few words. For example, a text may be republished with a slightly different headline on the same day and therefore be included twice in online archives. To reassure that duplicate texts where removed, we employed a text similarity approach based on vector space modeling similar to previous

studies (Boumans et al., 2018; Welbers et al., 2018): Articles were modeled as vectors in a space based on their feature frequencies, i.e., their relative location to each other was based on the occurrence of words in each article. The cosine similarity measure was then used to calculate the distance between vectors, indicating in how far articles share the same features such as words. For example, a very low cosine similarity close to 0 would indicate that two articles do not share any features. A high cosine similarity close to 1 would indicate that two documents share exactly the same features. If the cosine similarity between a pair of articles was above .9, one of the texts was removed, as this threshold proved to be efficient during manual inspection of duplicates.

Removal of Irrelevant Content. By retrieving articles based on the singular occurrence of search terms such as "climate change", our corpus might include articles that do not deal with climate change as their main topic but only mention search terms in passing. Especially when analyzing texts automatically, this might introduce serious noise to the analysis (Grundmann, 2021). To assure the minimization of such noise, we tested the validity of our search terms similar to Liu et al. (2011). We created a broader list of search terms based on which we retrieved coverage related to climate change but also articles where the issue is only mentioned in passing or not at all. English or German language search terms were deduced from an overview study by Schmidt et al. (2013) and included the following terms:

"*tuvalu* or climate change* or global warming* or globalwarming* or greenhouse* or pollution* or air pollution* or water pollution* or noise pollution* or animal protection* or klimawandel* or (global* and erwärmung*) or treibhauseffekt* or klimakatastrophe* or ipcc* or copenhagen* or kyoto* or forest* or two degrees* or carbon**"

We retrieved $N = 600$ news articles by outlets in our sample mentioning any of these terms at least once. Two coders manually coded these articles for whether climate change was the main topic of an article to create a manual benchmark ($\alpha = .96$). Articles were manually classified as reporting on climate change as their main topic if they explicitly and primarily covered climate change, its causes, its consequences, solutions, and measures against it in at least one paragraph. The sample was balanced, i.e., it included articles mentioned climate change as their main topic (true positives: 48.33%) or in passing/a completely different context (true negatives: 51.67%) to a similar degree. We then tested how well our search terms worked for precisely retrieving almost all articles where climate change is the main issue compared to the manual benchmark. First, we checked the share of articles truly covering climate change as the main topic (according to the manual benchmark) in all articles classified to be displaying

the issue as the main topic (according to the automated retrieval of articles based on search terms in the main study). This value, called precision, indicates how well our sampling approach did at only classifying truly relevant articles as such out of those that were classified as being relevant (true positives and false positives retrieved via our search terms). The higher this value, the better our sampling approach in terms of only selecting articles where climate change is the main topic. We also checked the share of articles truly covering climate change (according to the manual benchmark) out of all articles correctly classified to be covering climate change and those falsely classified to not be covering climate change (according to the automated retrieval of articles based on search terms in the main study). This value, called recall, indicates how well our approach did at retrieving all relevant articles (true positives) out of those that should have been retrieved (true positives retrieved and false negatives not retrieved via our search terms). The higher this value, the better our sampling approach in terms of finding all articles where climate change is the main topic. The harmonic mean of precision and recall, called F_1, was also calculated.

A precision/recall test indicated that our sampling approach was valid. Almost all articles that were relevant were retrieved without falsely classifying to many irrelevant articles as relevant (precision = .85, recall = .98, F_1 = .91). Recall was better than precision, which means that our sampling approach finds almost all articles where climate change is the main topic but also includes some articles (although few) where this is not the case. However, articles not explicitly dealing with climate change as their main topic (false positives which led to lower precision, for example articles mentioning climate change only in passing) were further excluded through our structural topic modeling approach as described later. Hence, we decided to optimize recall over precision.

Appendix B. Measurement of Variables Related to Issue Attention

To answer RQ1 to RQ3, we constructed one dependent and several independent variables. An overview of these variables, how they were constructed, and which sources were used is given in Table B1.

B1. Levels of Issue Attention across Countries (RQ1)

Our dependent variable (*Issue Attention*$_{t,i}$) measures the percent of climate change related coverage compared to the entirety of coverage in a given month$_t$ in a given country$_i$. We used this variable to calculate the mean level of issue attention across countries (RQ1).

B2. Development of Issue Attention across Countries (RQ2)

Next, we created a set of independent variables to model issue attention over time in a panel setting. This includes the variable *Time Trend*$_t$ (T = 1, 2, …, 156) which was used to analyze whether we find an increase or a decrease in issue attention over time (RQ2).

B3. Association with Focusing Events across Countries (RQ3)

We also included a variety of political, economic, scientific, and societal focusing events to analyze whether issue attention is associated with focusing events (RQ3). While many panel models only include lagged variables, most independent variables were not lagged due to the fact that cross-correlations between dependent and independent variables indicated an imminent effect (potentially due to the fact that we observe attention on a less fine-grained level, specifically on a monthly basis). For example, a focusing event may have occurred in the beginning or midst of a month and was thus expected to be associated with increased media attention within the same month. Thus, a lagged effect (an effect of a focusing event on issue attention in the next month) was neither likely theoretically nor indicated by cross-correlations. In some cases, however, events occurred at the end of a month, which led us to expect a lagged effect, and cross-correlations between dependent and independent variables also indicated that lags of independent variables should be included. If an independent variable was lagged, this is indicated through the subscript of this variable's name as $_{t-x}$. For example, the variable *Stern Report*$_{t-1}$ describes a lagged effect, i.e., whether the Stern report was published one month prior to the point of observation of *Issue Attention*$_{t,i}$. The report was published at the end of October 2006 and thus an imminent effect on issue attention in October was neither likely nor indicated by cross-correlations by this variable and the dependent variable. Thus, we tested for

associations between issue attention in month *t* and publication of the Stern report in the previous month *t-1* and included the lagged effect as *Stern Report*$_{t-1}$.

Concerning political focusing events, we included three variables. The variable *COPs*$_t$ describes the share of days the COP took place during a given month (United Nations, 2020) similar to previous studies (Grundmann and Scott, 2014; Liu et al., 2011; Schäfer et al., 2014). *G7/G8 Summits*$_t$ describes whether a G7/G8 summit took place in a given month (Liu et al., 2011; Sampei and Aoyagi-Usui, 2009; Schäfer et al., 2014). The variable *US Withdrawal from the Paris Agreement*$_t$ described whether US president Donald Trump withdrew from the Paris agreement in a given month as similar policy decisions such as the non-ratification of the Kyoto protocol also led to peaks in attention (Bohr, 2020).

Concerning economic focusing events, the variable *Stern Report*$_{t-1}$ describes whether the Stern report was published in the previous month as the report is associated with heightened issue attention (Grundmann and Scott, 2014). As the Stern report was published at the end of October 2006, we tested for a lagged effect.

Concerning scientific focusing events, we included four variables. The variable *Climate Gate*$_t$ and *Climate Gate*$_{t-1}$ describe whether the hacking of emails related to the Climatic Research Unit occurred in the same month or the month prior to the point of observation. The scandal is assumed to have been heavily covered (Grundmann and Scott, 2014; Holliman, 2011) and to have influenced trust towards science (Leiserowitz et al., 2013). Cross-correlations indicated that "Climate Gate" might have had a contemporaneous *and* a delayed effect, i.e., might have influenced issue attention within the month of the event and a month later. The variables *IPCC Reports (Final)*$_t$ and *IPCC Reports (Working)*$_t$ describe whether a final IPCC report or a working report were published in a given month (IPCC, 2020) based on previous studies (Liu et al., 2011; Schäfer et al., 2014). We differentiated between final and working reports as these are assumed to impact issue attention to different degrees.

Concerning *societal focusing events*, we included five variables. *Release of Movies*$_{t,i}$ describes whether a popular climate change related movie was released in a given month in the respective country, i.e., national release dates. Out of the most popular movies dealing with climate change or global warming according to the ImbD (ImbD, 2020), expert members of the research team decided on the inclusion of movies based on two criteria: First, movies needed to focus on climate change as their main topic. Second, we only include movies shown to be influential according to previous analyses (Brulle et al., 2012; Schäfer et al., 2014), or, especially for more recent releases that have not been included in pertinent analyses, to be

highly popular based on votes on IMDB and their box-office grosses (ImbD, 2020). We thus coded whether any of the following eight movies were released in a given month in the respective country: "An Inconvenient Truth" (2006) and the follow-up movie "An Inconvenient Sequel" (2017), "Before the Flood" (2016), "Cool it" (2010), "Geostorm" (2017), "Merchants of Doubt" (2014), "The 11th Hour" (2007), and "The Great Global Warming Swindle" (2007). Next, the variable *Live Earth Concert*$_t$ describes whether the Live Earth Concert took place in a given month similar to previous analyses (Schäfer et al., 2014). *Earth Hour*$_t$ describes whether the Earth Hour took place in a given month since the event is often covered (Keller et al., 2020). *Celebrity Events*$_t$ describes whether celebrities received prizes for their climate change engagement in a given month – specifically, Al Gore and the IPCC receiving the Nobel price, Al Gore's movie "An inconvenient Truth" receiving the Academy Award, the pope's publication of the encyclical "Laudato si", or Leonardi di Caprio drawing attention to climate change in his 2016 Academy Award speech based on previous studies (Bohr, 2020; Leas et al., 2016; Schäfer et al., 2014). Lastly, we also coded for a number of environmental protests that took off throughout the end of our observation period. *Protests*$_t$ describes whether one of these prominent protests – specifically, the Fridays for Future strikes, the Global Climate March, the People's Climate March, or Extinction Rebellion members blocking prominent spots in the UK – took place in a given month given peaks in attention due to similar events (Thorson and Wang, 2020).

Lastly, we controlled for factual indicators of climate change as well as national characteristics, such as a country's stance towards the issue of climate change, as these also influence issue attention to some extent (Barkemeyer et al., 2017; Boussalis et al., 2016; Liu et al., 2011; Schäfer et al., 2014). *National Deaths (log)*$_{t-1,i}$ and *Worldwide Deaths (log)*$_{t-1}$ describe the number of deaths and missing people due to extreme natural disasters in a given country or worldwide in the month prior to each point of observation according to the International Disaster Database (Guha-Saphir, 2020). *National Damages (log)*$_{t-1,i}$ and *Worldwide Damages (log)*$_{t-1}$ draw on the same database but describe financial damages caused by an extreme natural disaster in a given country or worldwide in the month prior to the point of observation. Due to their skewness, we took the log of the original variables. We also included *Country Fixed Effects*$_i$ to account for national, time-invariant characteristics and *Lags of Previous Media Attention*$_{t-1,t-2,t-3,t-4,i}$ to control for continuity in coverage, i.e., issue attention being a function of issue attention in previous months. We included these lags as pre-estimation of lag-order selection showed lags for up to four months to be influential.

Table B1. Operationalization of Variables

Variable	Description	Measurement	Source
Dependent Variable			
Issue Attention$_{t,i}$	Percentage of climate change related coverage compared to all coverage in a given month in a given country	Numeric value	News dataset
Independent Variables			
Time Trend			
Time Trend$_t$	Time point of observation, from 1 (January 2006) to 156 (December 2018)	Numeric value	
Political Focusing Events			
COPs$_t$	Share of days in a given month the COP took place	Numeric value	United Nations (2020)
G7/G8 Summits$_t$	Whether a G7/G8 summit took place in a given month	0 = No, 1 = Yes	Specific dates via news
US Withdrawal from the Paris Agreement$_t$	Whether Trump withdrew from the Paris agreement in a given month	0 = No, 1 = Yes	Specific date via news
Economic Focusing Events			
Stern Report$_{t-1}$	Whether the Stern report was published in the month prior to the point of observation	0 = No, 1 = Yes	Specific date via news
Scientific Focusing Events			
Climate Gate$_t$ *Climate Gate*$_{t-1}$	Whether the Climate Gate scandal occurred in the same month or the month prior to the point of observation	0 = No, 1 = Yes	Holliman (2011)
IPCC Reports (Final)$_t$	Whether a final IPCC assessment was published in a given month	0 = No, 1 = Yes	IPCC (2020)
IPCC Reports (Working)$_t$	Whether an IPCC working report was published in a given month	0 = No, 1 = Yes	IPCC (2020)

Societal Focusing Events

Release of Movies$_{t,i}$	Whether any of the following movies were released in a given month in the respective country: - An Inconvenient Truth - An Inconvenient Sequel - Before the Flood - Cool it - Geostorm - Merchants of Doubt - The 11th Hour - The Great Global Warming Swindle	0 = No, 1 = Yes	ImbD (2020)
Live Earth Concert$_t$	Whether the Live Earth Concert took place in a given month	0 = No, 1 = Yes	Specific dates via news
Earth Hour$_t$	Whether the Earth Hour took place in a given month	0 = No, 1 = Yes	Specific dates via news
Celebrity Events$_t$	Whether any of the following events took place in a given month: - Nobel peace prize for Al Gore/IPCC - Publication of the encyclical "Laudato Si" by the Pope - Academy Award speech on climate change by Leonardo di Caprio - Academy Award for Al Gore's documentary "An inconvenient truth"	0 = No, 1 = Yes	Specific dates via news; Leas et al. (2016)
Protests$_t$	Whether any of the following events took place in a given month: - Fridays for Future protests - Global Climate March - People's Climate March - Extinction Rebellion protests	0 = No, 1 = Yes	Specific dates via news

Control Variables

National Deaths $(log)_{t-1,i}$	Log of number of deaths and missing people due to natural disasters occurring in the month prior to the point of observation in the respective country	Number of deaths	Guha-Saphir (2020)
Worldwide Deaths $(log)_{t-1}$	Log of number of deaths and missing people due to natural disasters occurring in the month prior to the point of observation worldwide	Number of deaths	Guha-Saphir (2020)
National Damages $(log)_{t-1,i}$	Log of damages/economic losses directly or indirectly due to natural disasters occurring in the month prior to the point of observation in the respective country	US-Dollar, in 1,000$	Guha-Saphir (2020)
Worldwide Damages $(log)_{t-1}$	Log of damages/economic losses directly or indirectly due to natural disasters occurring in the month prior to the point of observation worldwide	US-Dollar, in 1,000$	Guha-Saphir (2020)
Country Fixed Effects$_i$	Dummy variable for each country	0 = No, 1 = Yes	
Lags of Previous Media Attention$_{t-1,t-2,t-3,t-4,i}$	Relative frequency of media coverage in four months prior to the point of observation in the respective country	% of articles covering climate change	News dataset

Appendix C. Exclusion of Background Topics

To decide which topics to keep and which to exclude as so-called background topics, members of the research term were supplied with a variety of information on each of our K = 85 topics. In particular, they received specific coding instructions and a separate sheet containing information on each topic (see example in Table C1). To illustrate how researchers may decide whether to keep or discard a topic for further analysis, translated excerpts from the coding instructions and the information sheets are discussed in the following sections.

Coders received the following coding instruction (translated from German to English): "*Please decide whether the following topics should be considered a background topic which should be excluded from further analysis. Background topics are topics that do not describe a consistent topic, are incomprehensible, or that do not mainly focus on climate change. Please consider the following list of information on each topic for your decision. If you think that a topic is coherent, comprehensible, mainly focuses on climate change and should thus be kept for further analysis, please code "1". If you think that a topic should be considered a background topic and excluded from further analysis, please code "0"*."

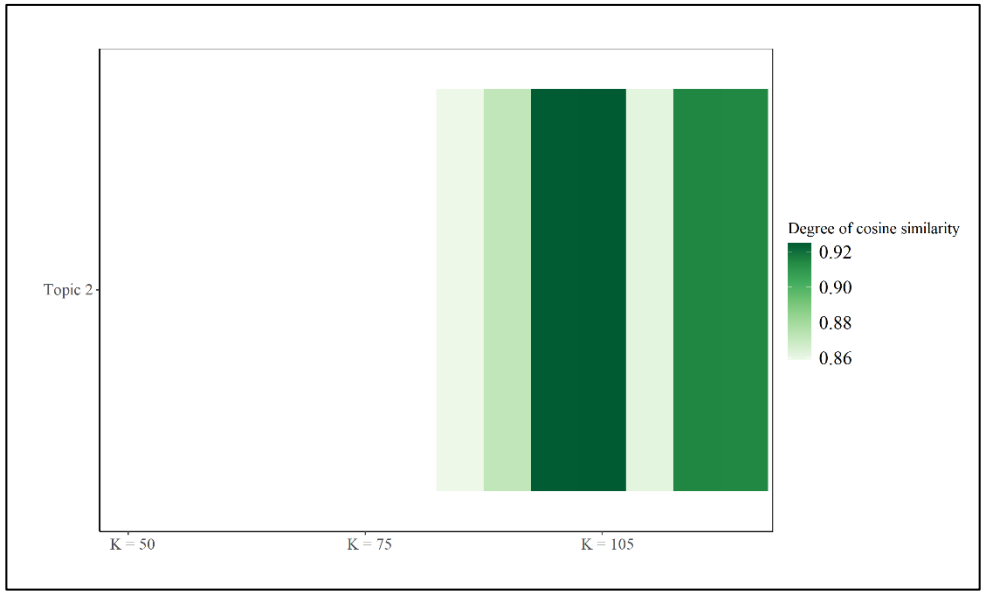
Indicators for Background Topics

- **Top Terms**: Top Terms describe features that are characteristic for a topic as they are both frequent in and exclusive for the respective topic. Incoherent top terms indicate a background topic.
- **Top Documents**: Top Documents are randomly sampled articles in which this topic is prevalent with a comparably high conditional probability (above 30%). Please read the documents referenced here. If these do not seem to describe a coherent topic, this indicates a background topic.
- **Rank-1 metric**: The Rank-1 metric describes how many articles in the corpus were assigned this topic as their main topic (both in absolute and relative values). The lower the Rank-1 metric, the less often this topic is the main topic across all articles. A low Rank-1 metric thus indicates a background topic.
- **Robustness of topic across K**: Figure 1 describes how often the topic that was found in the model with K = 85 topics was reproduced across other models with different choices for K – for example, whether we found the same topic when calculating a model

with $K = 75$ or $K = 95$ topics. Green spaces indicate that the topic was reproduced for other choices of K, white spaces indicate that the topic was not reproduced for other choices of K. The darker the green color, the higher the cosine similarity between the topic in our model with $K = 85$ and the topic that was found to be a match in a model with a different choice for K. If a topic is rarely reproduced for other choices of K, this indicates it not being very robust and thus a background topic. In short, the more white spaces a figures contains, the less reproducible a topic, which indicates a background topic.

Table C1. Information Sheet for Exemplary Topic

Information on Topic 2 from the model with K = 85 topics	
Top Terms	*Please see the following top terms:* lights, awareness, earth hour, wwf, campaign, hour, earth, switch, concert, initiative, raise, organisers, stadium, launched, bangkok, launch save, switched, switching, message
Top Documents	*Please read the following documents:* Hindu_2009-9-9_718.txt; NZHerald_2008-07-21_2538.txt; The Nation_2015-3-26_23512.txt; NZHerald_2009-03-30_1901.txt; Hindu_2008-5-3_1601.txt; Toronto Star_2008-4-17_1923.txt; The Star_2018-3-9.txt; The Sydney Morning Herald_2009-3-17_33364.txt; Hindu_2012-3-22_4051.txt ; Hindu_2009-9-8_720.txt
Rank-1 Metric	Absolute (N = Number of articles): 618 Relative (% of articles in corpus): .86%
Robustness of Topic across K	*Figure 1: Robustness of topic for different choices of K*



Appendix D. Validity & Robustness of Results

A range of studies have stressed limitations of approaches related to automated content analysis, including topic modeling (Brookes and McEnery, 2019; Grundmann, 2021; Maier et al., 2018; Song et al., 2020). Topic modeling in particular may be sensitive to a lack of linguistic sensitivity, i.e., the danger of interpreting topic based on a list of top terms without any manual inspection. As such, these debates relate to larger discussions about the validity of results generated by automated content analyses (Song et al., 2020). Moreover, topic modeling also suffers from a lack of replicability and robustness, i.e., models converging to different solutions or results being dependent on parameter settings, which relates to larger discussions about the robustness of results generated by automated content analyses (Nelson, 2019). In the following sections, we will discuss how we reassured the validity and robustness of results.

D1. Validity Tests

Scholars have criticized that studies often do not sufficiently check if they measure what they claim to measure (i.e., the validity of their results). To reassure the validity of results, we followed recent recommendations: First, we conducted in-depth readings of articles instead of simply using top terms for interpreting and labeling topics as recommended by Brookes and McEnery (2019). As described in Appendix C1, each team member read ten articles which had a comparably high conditional probability for each topic. This information was used in addition to, for example, the top terms of each topic to interpret topics.

A second recommendation for reassuring the validity of results is that scholars should validate their findings through comparison to, for example, a manually coded gold standard (Song et al., 2020), something that is rarely done in studies in the field of climate change communication (for a recent exception, see Boussalis et al., 2016). Thus, we compared the automated classification of themes and dimensions to manual benchmarks created by team members and external coders in two separate validity tests. Two members of the research team coded the *expert manual benchmark* (N = 300); two graduate students who were not involved in any part of the data analysis coded the *external manual benchmark* (N = 442). For each validation test, we drew a stratified sample of articles. This sample consisted of articles that were assigned a clear theme or dimension as well as articles that displayed high probabilities for one of the background topics and were thus not assigned a clear theme or dimension according to the automated classification. Both coding teams were asked to assign up to two

themes to each article, with a second theme only being coded if they felt that this theme was prevalent to a similar amount than the first one (see coding instructions in Table D1). Intercoder reliability was found to be satisfactory for the detection of themes (expert manual benchmark: percent agreement: 83.3%, Krippendorff's $\alpha = .7$, $N = 30$; external manual benchmark: percent agreement: 74.4%, Krippendorff's $\alpha = .66$, $N = 45$). Please note that for the external manual benchmark according to Krippendorff's alpha, intercoder values are slightly lower than the recommended threshold of .7 (Song et al., 2020). However, since the second validation set meets the recommended threshold and both codings come to similar conclusions, we used both sets. We then compared the correct classification of our automated approach with both the expert and the external manual benchmark using aforementioned metrics on information retrieval, specifically the F_1 score as the harmonic mean of precision and recall.

Comparing automated results and the expert manual benchmark, we found automated classification to be satisfactory, except for the theme *Economic Impacts*. F_1 values amounted to $F_1 = .64$ for *Causes of & Solutions to Climate Change*, $F_1 = .59$ for *Climate Politics*, $F_1 = .71$ for *Awareness & Education*, $F_1 = .69$ for *Impact on Humans*, $F_1 = .22$ for *Economic Impacts*, $F_1 = .69$ for *Climate Change & Impacts on the Ecosystem*, and $F_1 = .7$ for *Climate Science*. When using the more aggregated dimensions, i.e., whether an article dealt with the societal dimension ($F_1 = .84$), the ecological dimension ($F_1 = .69$), or the scientific dimension ($F_1 = .7$), classification worked better. When comparing the automated content and the external manual benchmark, we came to similar conclusions. F_1 values amounted to $F_1 = .67$ for *Causes of & Solutions to Climate Change*, $F_1 = .66$ for *Climate Politics*, $F_1 = .65$ for *Awareness & Education*, $F_1 = .69$ for *Impact on Humans*, $F_1 = .44$ for *Economic Impacts*, $F_1 = .85$ for *Climate Change & Impacts on the Ecosystem*, and $F_1 = .6$ for *Climate Science*. Values for the societal dimension ($F_1 = .82$), the ecological dimension ($F_1 = .85$), and the scientific dimension ($F_1 = .6$) were higher. Overall, this indicates that the approach works sufficiently well for identifying broader dimensions in articles. However, for identifying more fine-grained themes an unsupervised approach may sometimes lack the necessary accuracy, as especially indicated by low validity values for the theme *Economic Impacts*.

Table D1. Description of Themes for Manual Validation

Theme	Description of Theme	Examples from Corpus
Awareness & Education	"*Awareness & Education*" describes how much citizens are aware of climate change, how they educate themselves about climate change, or engage in combating it. Articles displaying this theme may: • describe citizens' awareness through protests, activism, surveys concerning climate change • describe educational events/initiatives concerning (education about) climate change • describe ethical, philosophical, and societal debates about how to deal with climate change	(excluded due to copyright restrictions)
Causes of & Solutions to Climate Change	"*Causes of & Solutions to Climate Change*" focuses on what causes climate change and/or concrete measures to combat climate change. Articles displaying this theme may: • describe greenhouse gases, oil drilling, fracking, or other causes of climate change • describe measures to mitigate climate change (e.g., driving different cars, consuming less, using energy more efficiently, supporting different infrastructures in cities, punishing companies for irresponsible behavior)	(excluded due to copyright restrictions)
Climate Change & Impacts on the Ecosystem	"*Climate Change & Impacts on the Ecosystem"* describes climate changes and how it affects our ecosystem. Articles displaying this theme may: • describe extreme temperatures or weather events such as floods, droughts, wildfires, hurricanes • describe effects on the diversity of animals, seas, lakes, or plants, or changing landscapes (glaciers, seas, deserts, etc.)	(excluded due to copyright restrictions)

Climate Politics	*"Climate Politics"* describes climate change as a political issue that needs to be solved by political actions based on political summits, debates, and policies. Articles displaying this theme may: • describe political events in the form of COPs, international, regional, and national summits to combat climate change, • describe policies related to climate change and/or specific governmental stances towards climate change	(excluded due to copyright restrictions)
Climate Science	*"Climate Science"* focuses on the scientific nature of climate change by describing theories, research techniques, or scientific debates about the status quo and how to debate about climate change. Articles displaying this theme may: • detail scientific knowledge about climate change • illustrate scientific uncertainties about scientific knowledge concerning climate change	(excluded due to copyright restrictions)
Economic Impacts	*"Economic Impacts"* focuses on the economic impact of climate change and related policies as well as the energy industry. Articles displaying this theme may: • describe economic impacts of climate change on industries and companies • describe how the energy industry is developing	(excluded due to copyright restrictions)
Impacts on Humans	"*Impacts on Humans*" describes how climate change can affect humans in their daily lives. Articles displaying this theme may: • describe the increasing incidence of diseases such as asthma, allergies, or heat strokes • describe how climate change influence the way humans live, for example by threating their homes due to floods and rising sea levels • describe how climate change influences their nutrition, for example due to water scarcity or a decrease in agricultural development	(excluded due to copyright restrictions)

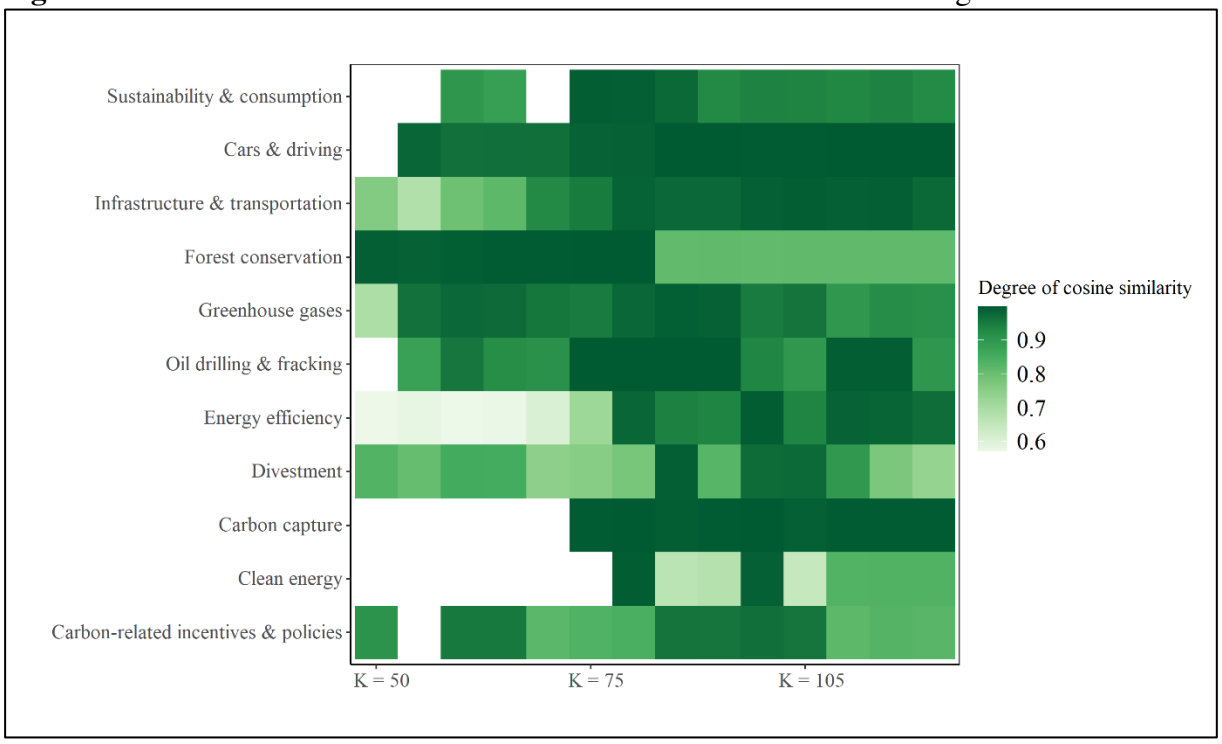
D2. Robustness Tests

Moreover, several scholars have stressed that topic modeling may suffer from a lack of replicability and robustness, i.e., models converging to different solutions across model runs or results being dependent on parameter settings (Brookes and McEnery, 2019), which relates to larger discussions about the robustness of results in this context (Nelson, 2019).

As Brookes and McEnery (2019, p. 5) argue "topics generated by the computer […] may be different each time the procedure is run". To reassure that this was not the case in our analysis, we employed spectral learning as a deterministic method for initialization. In short, this reassures that models do not vary across runs (Roberts et al., 2016).

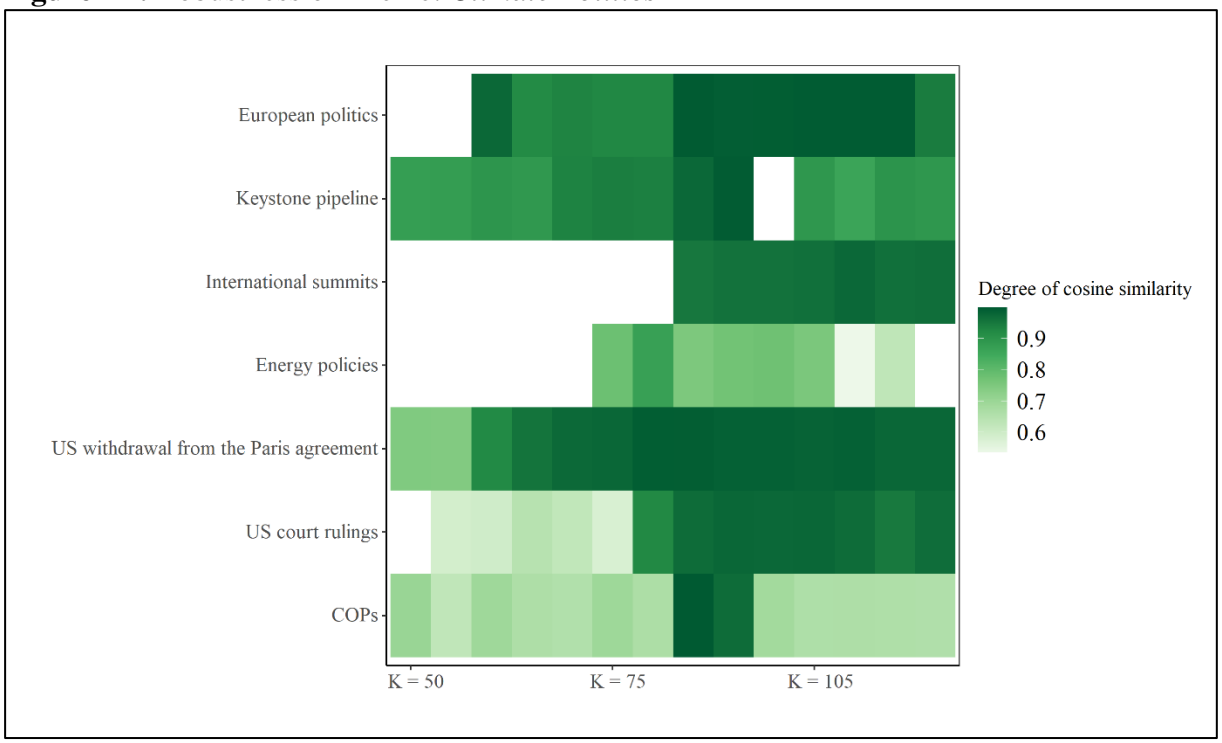
We also made sure that our results were not dependent on parameter settings. We agree with Wilkerson and Casas (2017, p. 541) that a "robust approach to reporting topic-model results takes advantage of the information provided by alternative specifications". Therefore, we first assessed whether topics related to themes we report in the paper (reference model, K = 85) can be reproduced across different specifications for K (robustness models, K = 50 to 120 in increments of K = 5). A topic was defined to be reproduced if the cosine similarity of the term-topic probability β-matrix for a topic of the reference model and the β-matrix of a topic in a robustness model exceeded .5. It is important to note that, due to these parameter settings, not all 85 topics can and will be reproduced across every parameter specification. For the robustness model with K = 50, only fifty topics will be calculated. Therefore, not all topics of our reference model with K = 85 can be reproduced simply since fewer topics can be matched. Hence, a topic's robustness is not indicated by it being reproduced across *all* specifications of K, but by it being reproduced across several settings for different K – the more, the less contingent the topic and the theme on the choice of K and the more robust the corresponding model. Figures D1-D7 illustrate the results of these robustness tests. For example, Figure D1 visualizes how often each topic connected to the theme *Causes of & Solutions to Climate Change* was reproduced across specifications of K, specifically K = 50 to K = 120. The darker the green color, the higher the cosine similarity between the topic in the reference model and the model in the robustness model, meaning the more similar the words news media use to cover this topic. For the example of the topic "Sustainability & consumption", we can see that the topic is very robust as it is reproduced steadily for K = 75 until K = 120. Overall, we find almost all themes and corresponding topics to be comparably robust independent of the choice of K.

Figure D1. Robustness of Theme: Causes of & Solutions to Climate Change



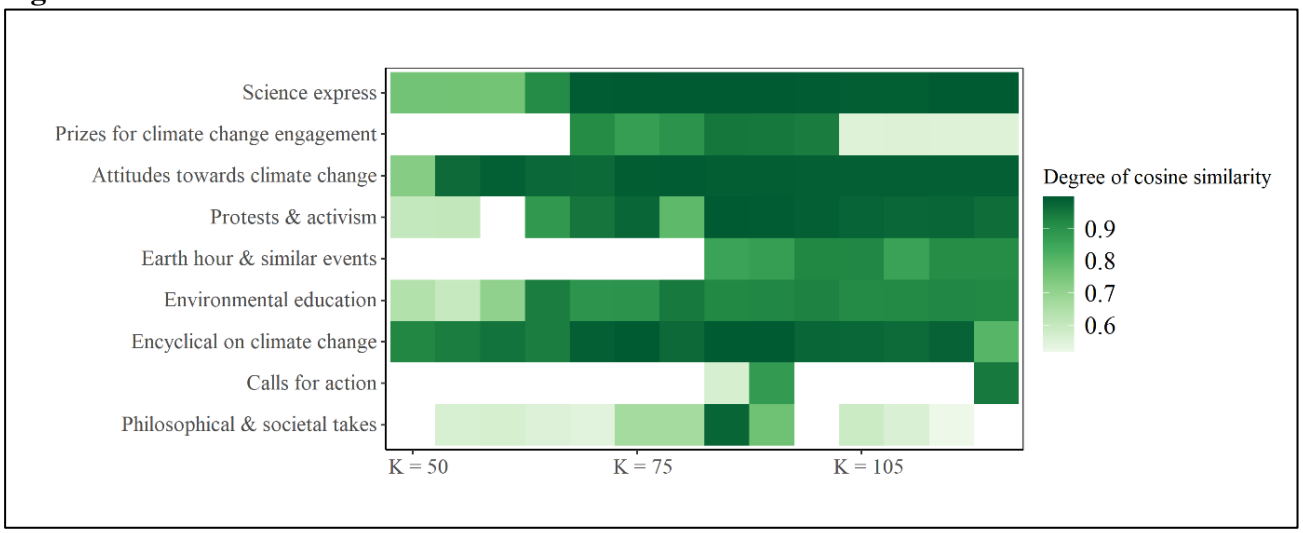
Note: Green spaces indicate that the topic in our reference model with $K = 85$ was reproduced in models with other K. Y-axis identifies topic in our reference model, x-axis identifies robustness model with different K. The darker the green, the higher the cosine similarity between top terms of topic in the reference model and the robustness models.

Figure D2. Robustness of Theme: *Climate Politics*



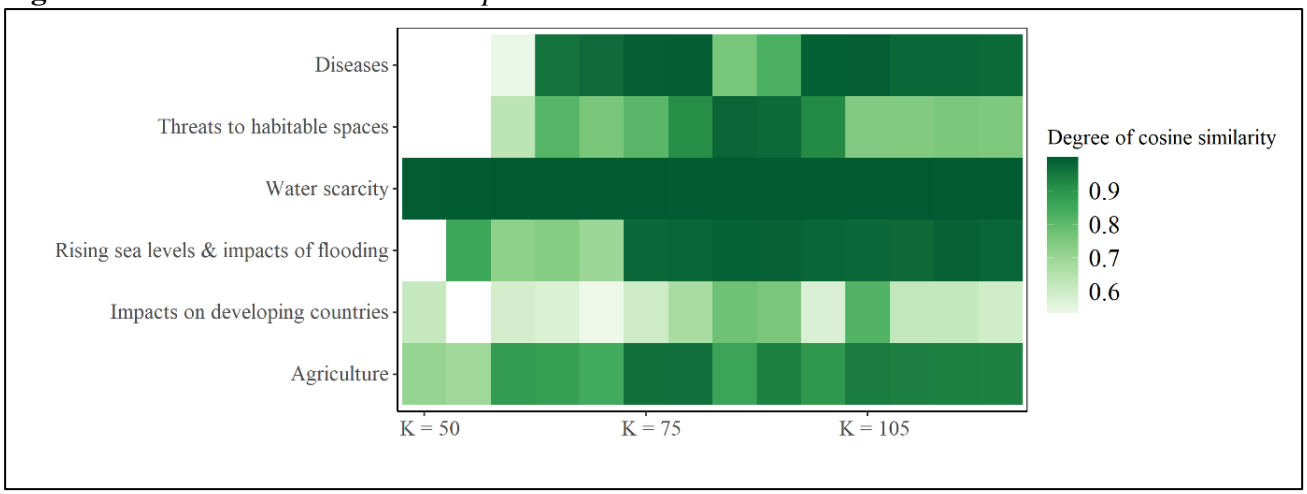
Note: Green spaces indicate that the topic in our reference model with $K = 85$ was reproduced in models with other K. Y-axis identifies topic in our reference model, x-axis identifies robustness model with different K. The darker the green, the higher the cosine similarity between top terms of topic in the reference model and the robustness models.

Figure D3. Robustness of Theme: *Awareness & Education*



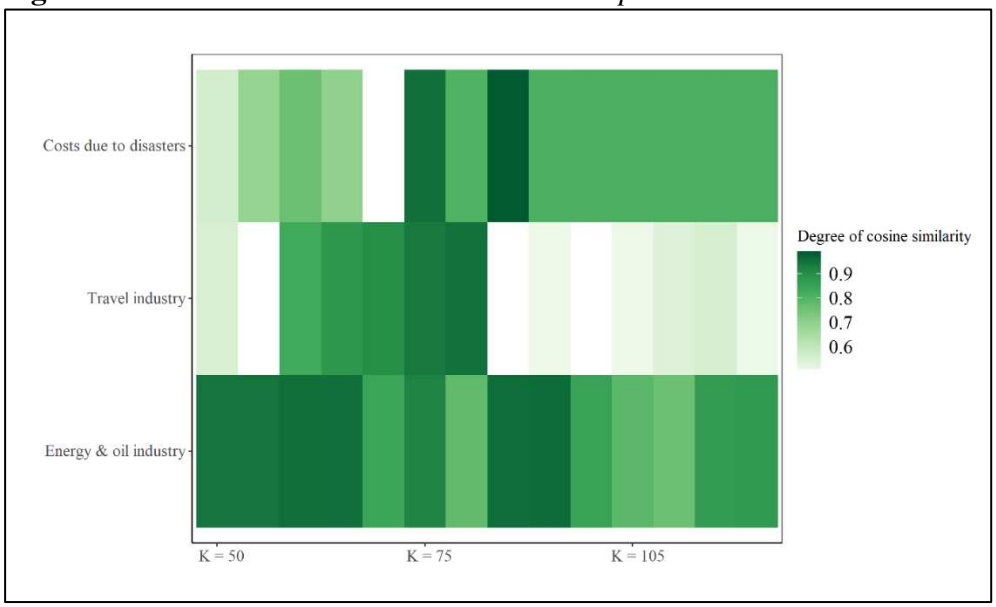
Note: Green spaces indicate that the topic in our reference model with $K = 85$ was reproduced in models with other K. Y-axis identifies topic in our reference model, x-axis identifies robustness model with different K. The darker the green, the higher the cosine similarity between top terms of topic in the reference model and the robustness models.

Figure D4. Robustness of Theme: *Impacts on Humans*



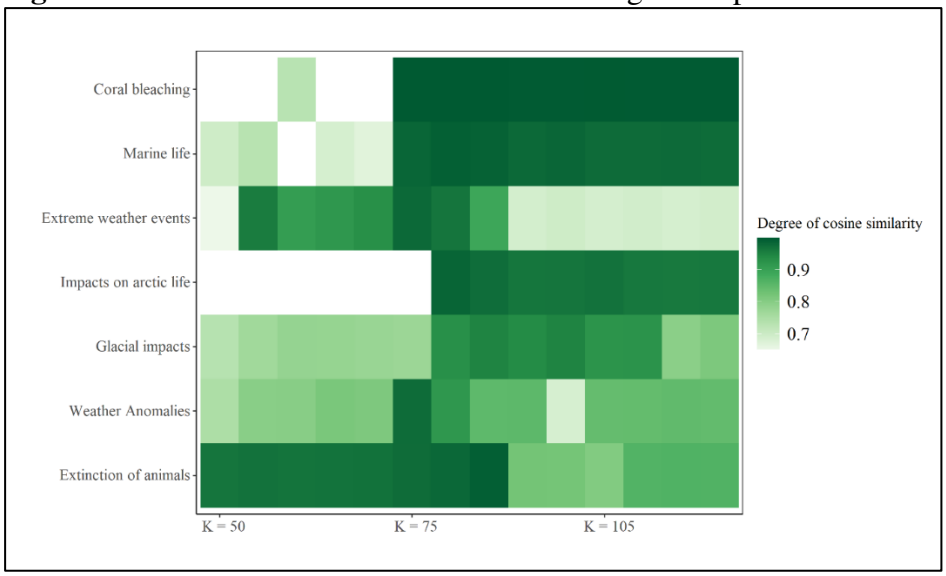
Note: Green spaces indicate that the topic in our reference model with $K = 85$ was reproduced in models with other K. Y-axis identifies topic in our reference model, x-axis identifies robustness model with different K. The darker the green, the higher the cosine similarity between top terms of topic in the reference model and the robustness models.

Figure D5. Robustness of Theme: *Economic Impacts*



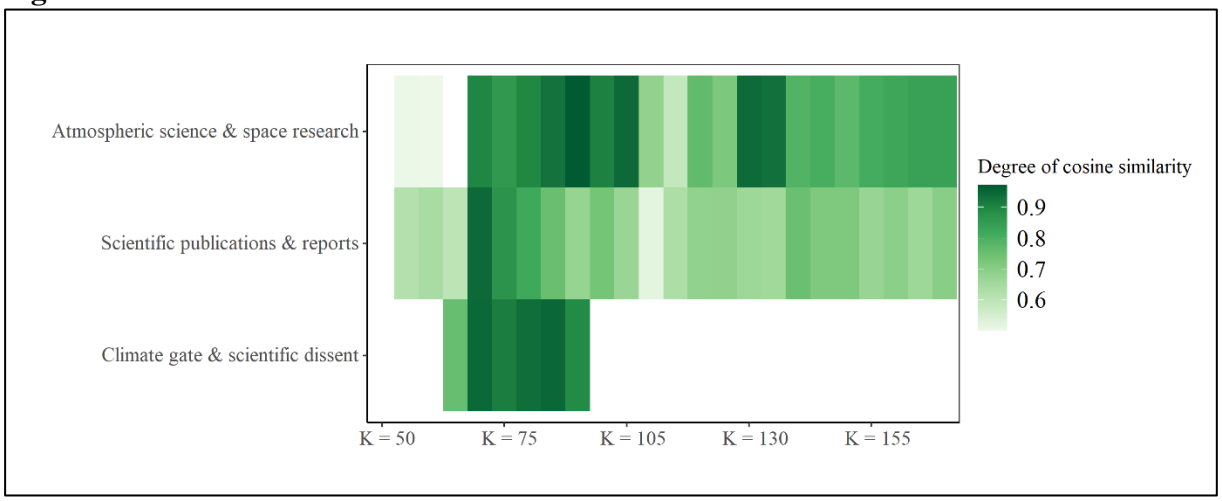
Note: Green spaces indicate that the topic in our reference model with $K = 85$ was reproduced in models with other K. Y-axis identifies topic in our reference model, x-axis identifies robustness model with different K. The darker the green, the higher the cosine similarity between top terms of topic in the reference model and the robustness models.

Figure D6. Robustness of Theme: Climate Change & Impacts on the Ecosystem



Note: Green spaces indicate that the topic in our reference model with $K = 85$ was reproduced in models with other K. Y-axis identifies topic in our reference model, x-axis identifies robustness model with different K. The darker the green, the higher the cosine similarity between top terms of topic in the reference model and the robustness models.

Figure D7. Robustness of Theme: *Climate Science*



Note: Green spaces indicate topic in our reference model with $K = 85$ was reproduced in models with other K. Y-axis identifies topic in our reference model, x-axis identifies robustness model with different K. The darker the green, the higher the cosine similarity between top terms of topic in the reference model and the robustness models.

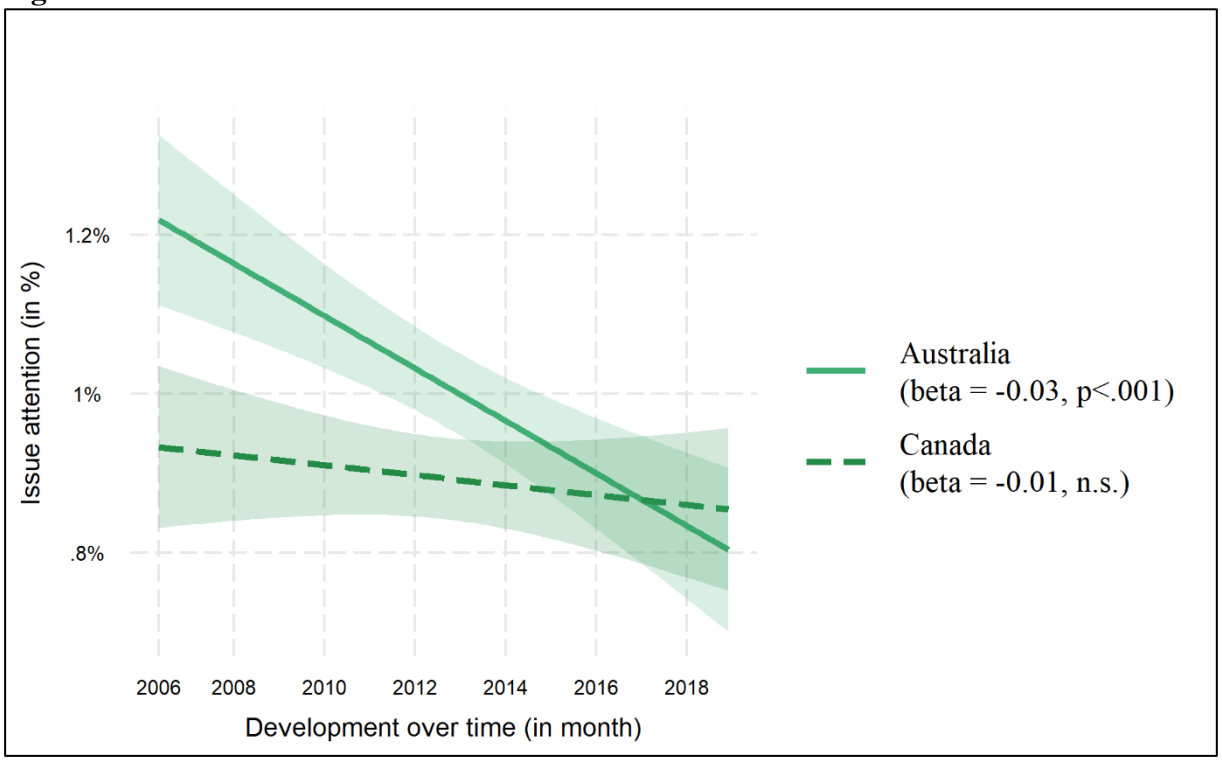
Appendix E. Interaction Models

Table 4 in the main paper summarized country-specific effects of time (RQ2) and focusing events (RQ3). For clarity and comprehensiveness, we visualize all interaction effects in the Supplementary Material and report whether or not these country-specific effects are consistent according to the Johnson-Neyman (J-N) test.

E1. Development of Issue Attention over Time (RQ2)

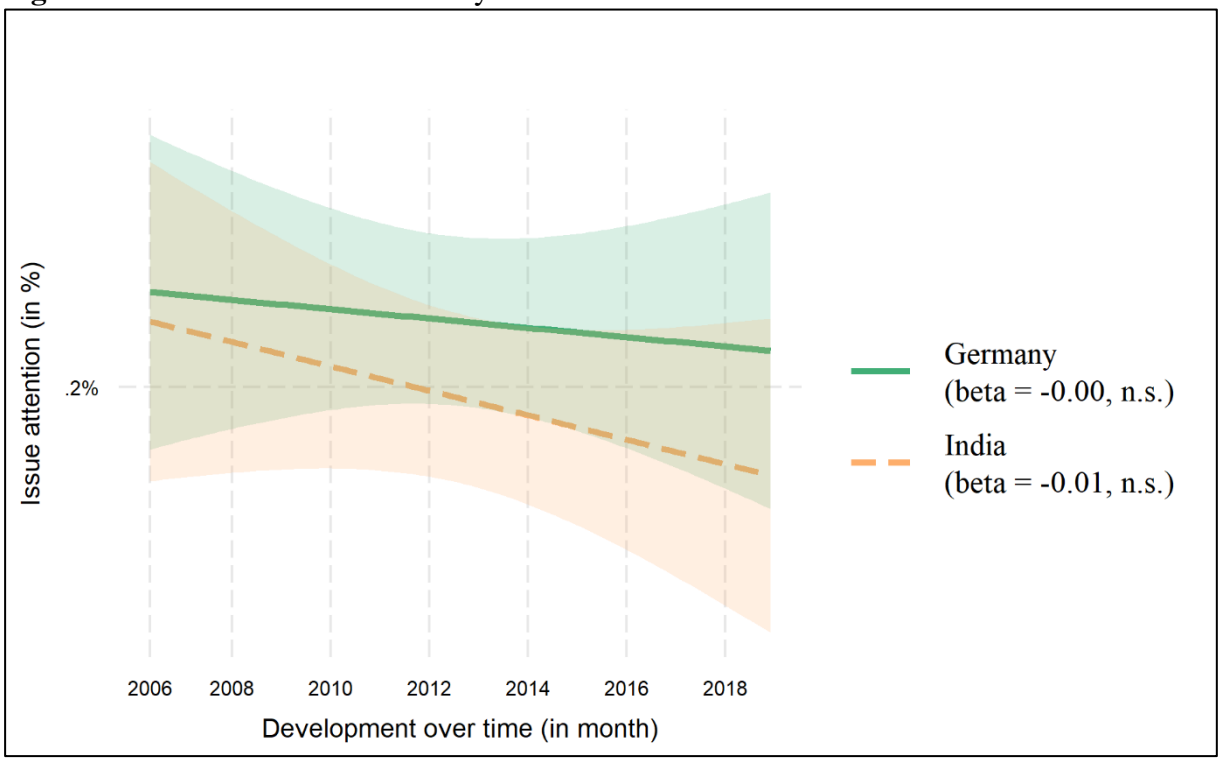
Starting with the effect of *Time Trend*$_t$ related to RQ2 first, we tested whether issue attention only increased in some countries but not in others. To do so, we included an interaction between country dummies and *Time Trend*$_t$. **In short, we found a consistent increase in Namibia, the UK, and the US as well as a consistent decrease in Australia.** No consistent trends were found for all other countries. Figures E1.1–E.1.5 visualize the corresponding effects and report the result of each J-N test, which indicates whether the simple slope for each country represents a consistent effect or not. If the J-N test is significant, this indicates a consistent trend within the specific country (p<.05), otherwise there is no consistent trend (n.s.). In all figures, countries from the Global North are depicted in green and countries from the Global South in orange.

Figure E1.1. Time Trend in Australia & Canada



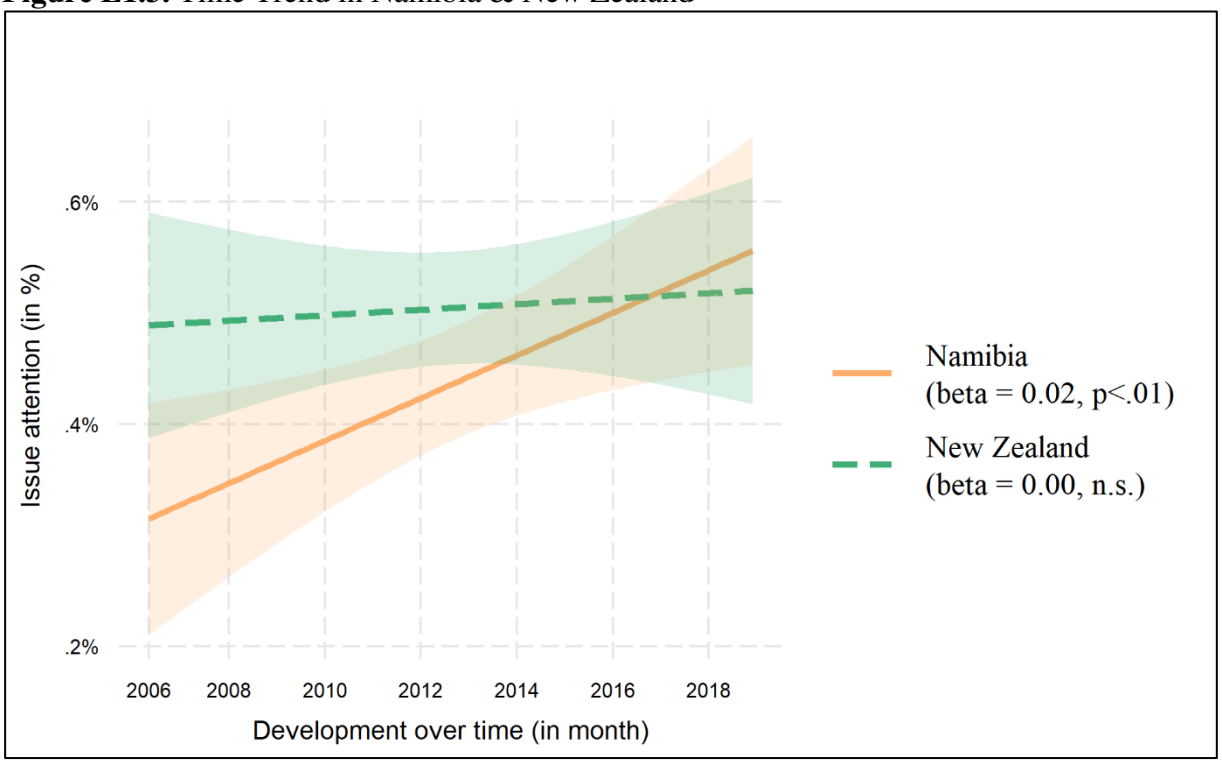
Note: Simple slopes of *Time trend*$_t$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E1.2. Time Trend in Germany & India



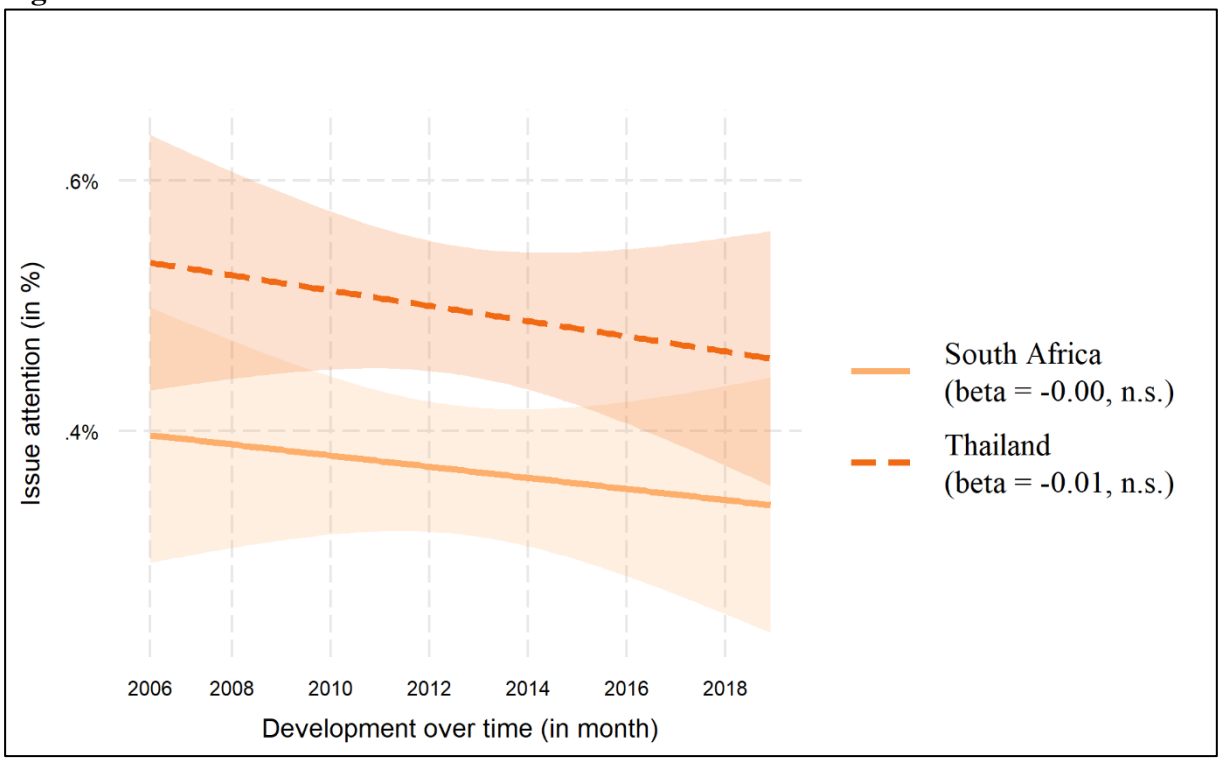
Note: Simple slopes of *Time trend*$_t$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E1.3. Time Trend in Namibia & New Zealand



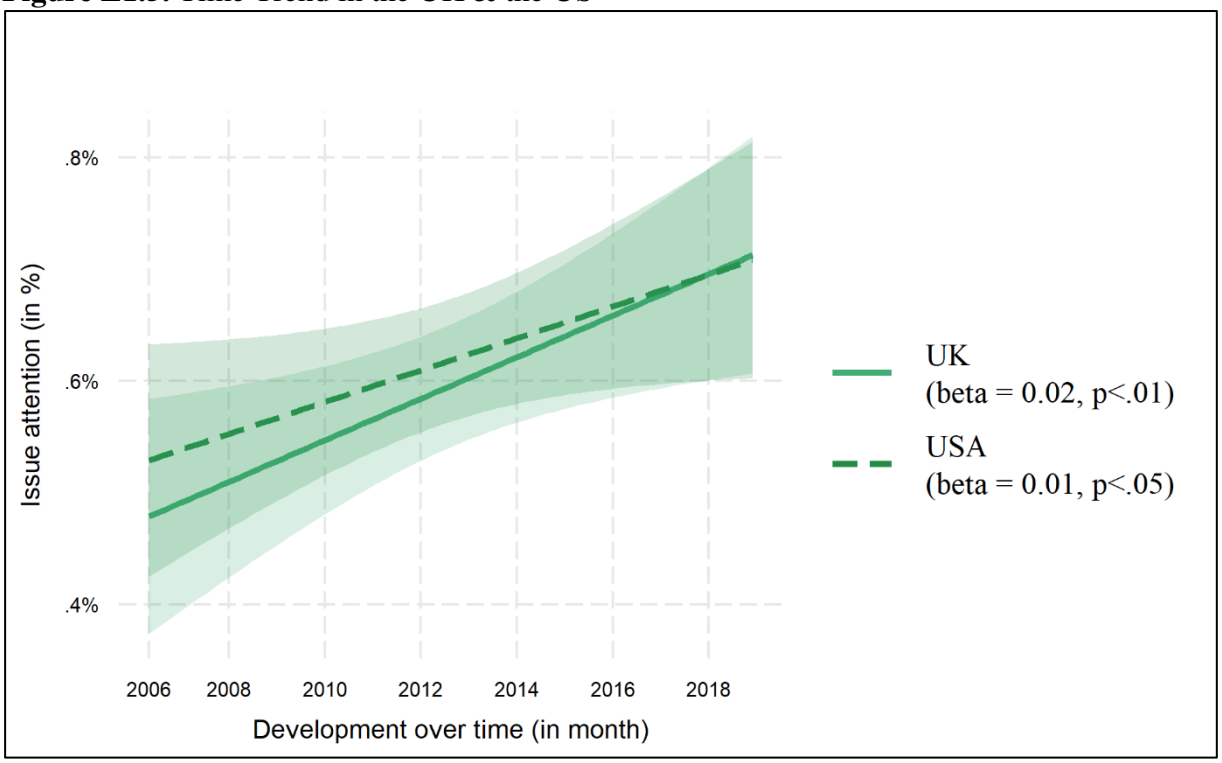
Note: Simple slopes of *Time trend*$_t$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E1.4. Time Trend in South Africa & Thailand



Note: Simple slopes of *Time trend*$_t$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E1.5. Time Trend in the UK & the US

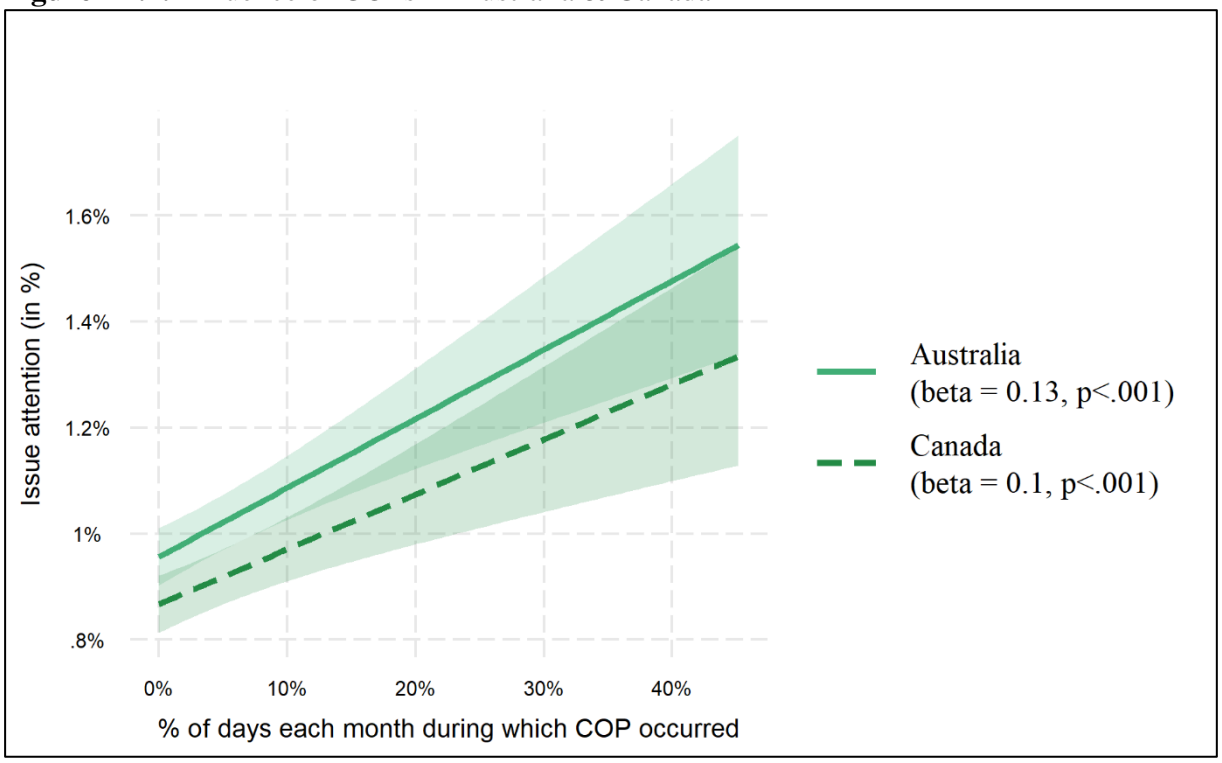


Note: Simple slopes of *Time trend*$_t$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

E2. Influence of Focusing Events across Countries (RQ3): COPs

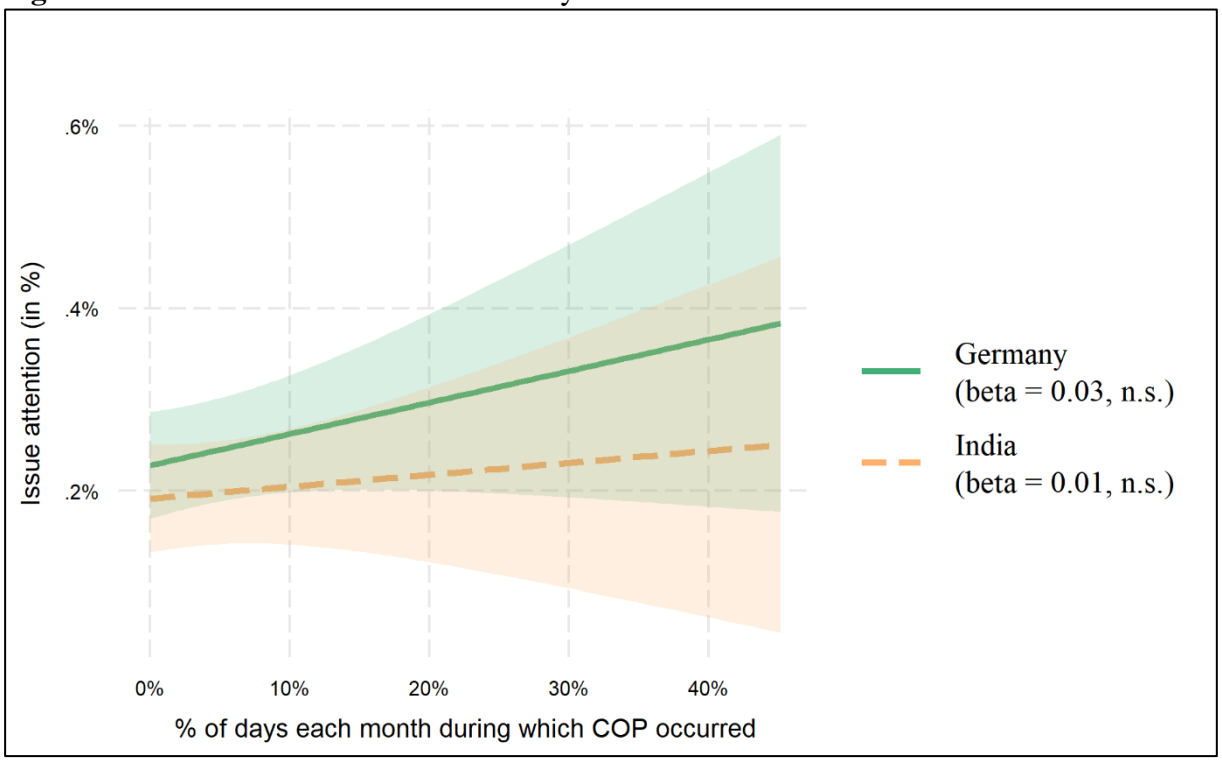
Turning to RQ3, we tested whether COPs were associated with peaks in issue attention in some countries but not in others. To do so, we included an interaction between country dummies and $COPs_t$. **In short, we found a consistent positive effect of COPs on issue attention in Australia, Canada, New Zealand, South Africa, Thailand, and the UK.** Figures E2.1–E2.5 visualize the corresponding effects and report the result of each Johnson-Neyman (J-N) test, which indicates whether the simple slope for each country represents a consistent effect or not. If the J-N test is significant, this indicates a consistent effect of COPs on issue attention within the specific country (p<.05), otherwise there is no consistent effect (n.s.). In all figures, countries from the Global North are depicted in green while countries from the Global South are depicted in orange.

Figure E2.1. Influence of COPs in Australia & Canada



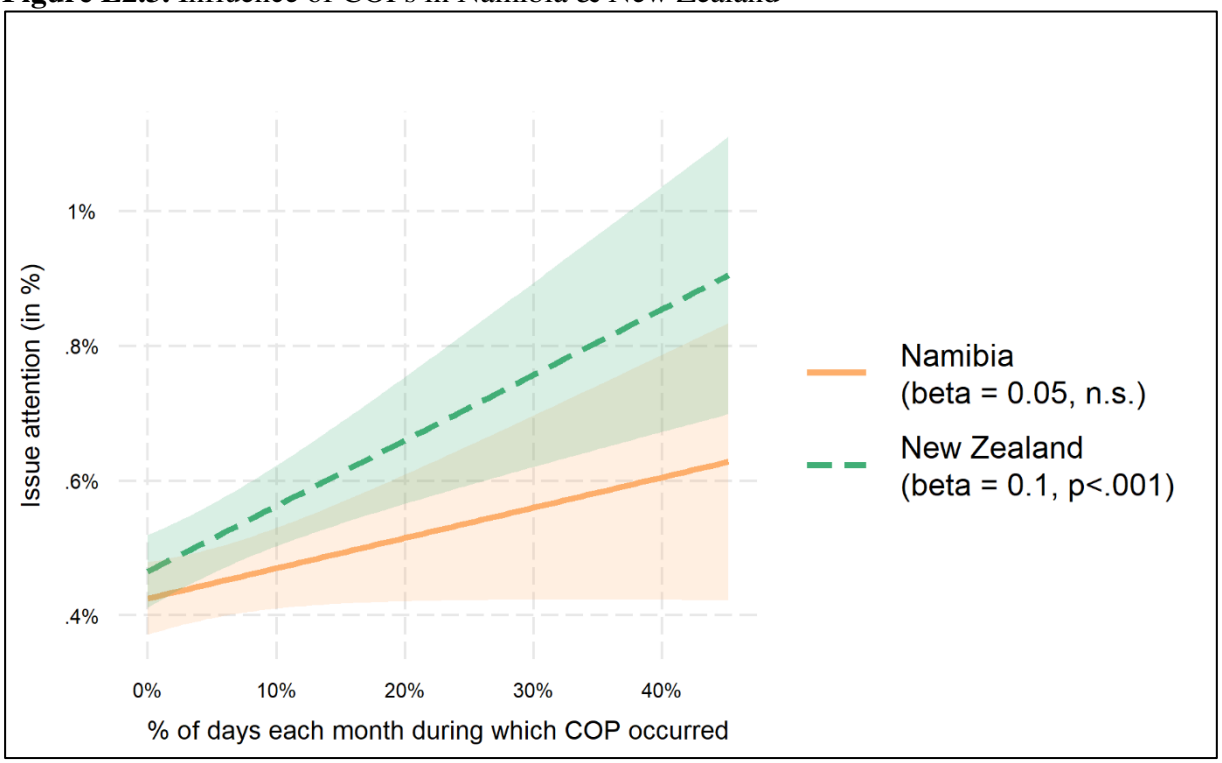
Note: Simple slopes of $COPs_t$ for each $country_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E2.2. Influence of COPs in Germany & India



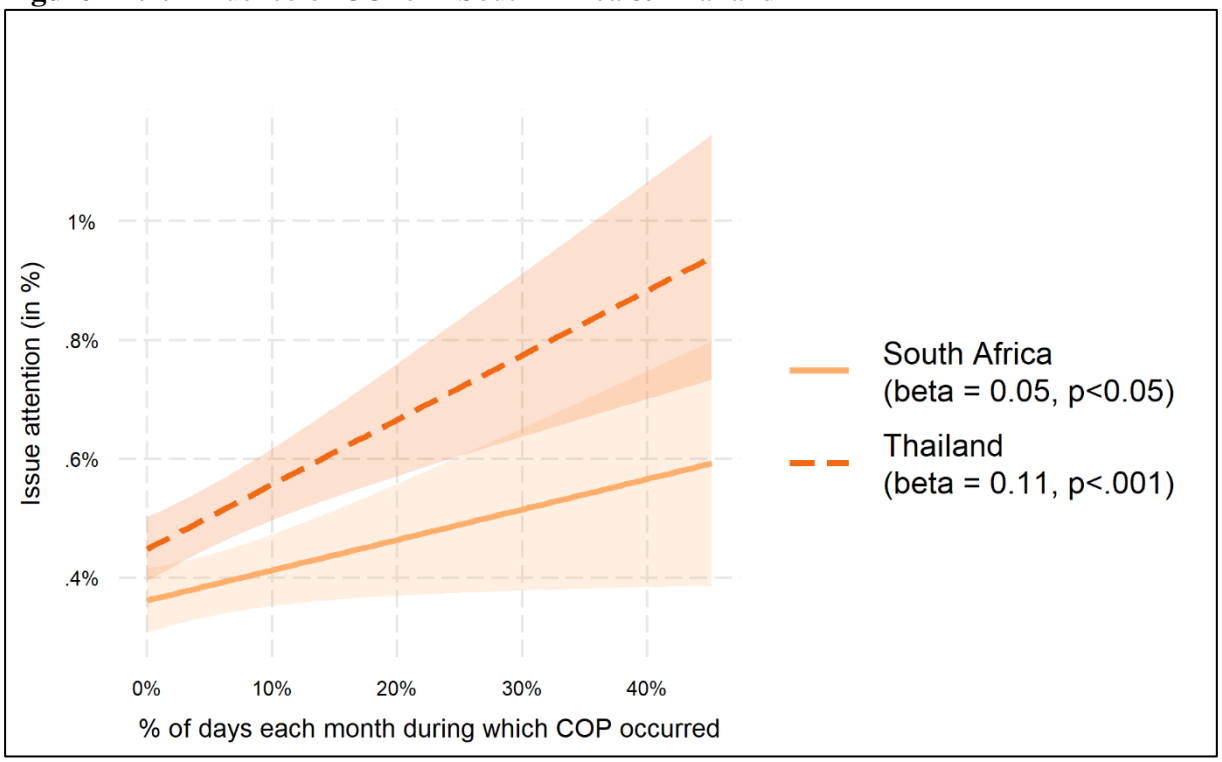
Note: Simple slopes of $COPs_t$ for each $country_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E2.3. Influence of COPs in Namibia & New Zealand



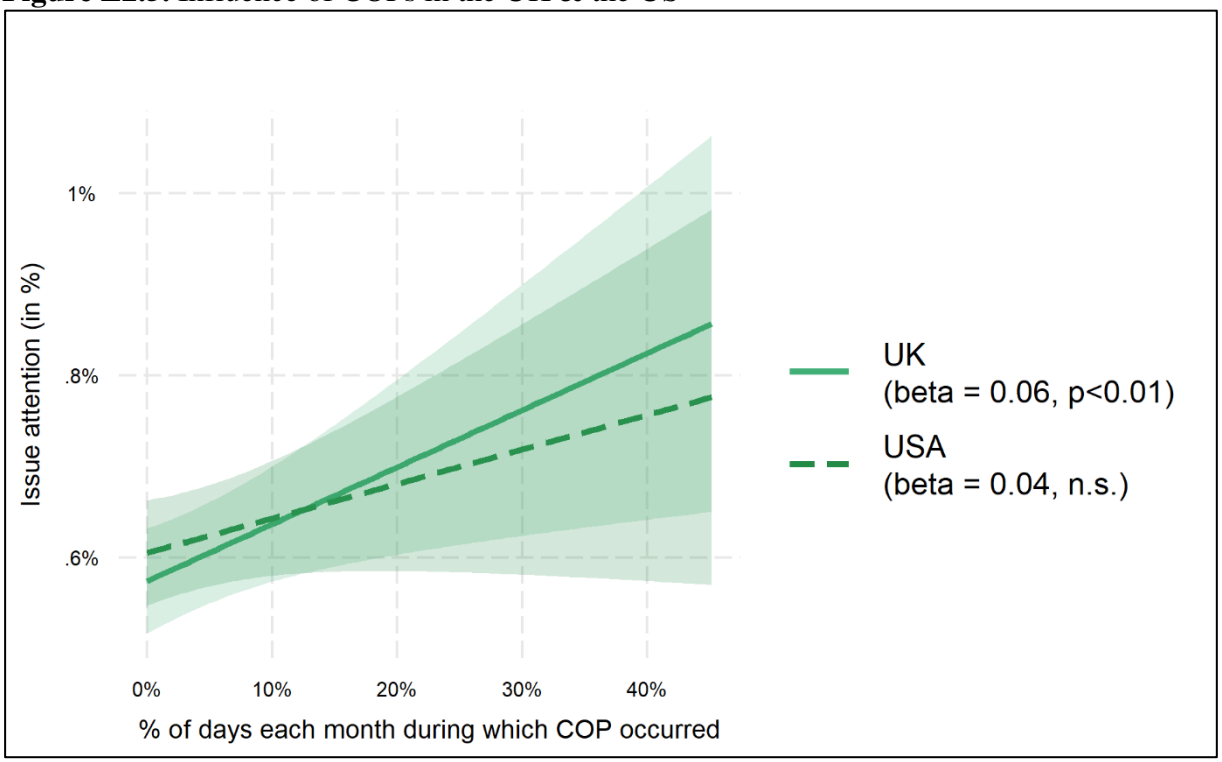
Note: Simple slopes of $COPs_t$ for each $country_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E2.4. Influence of COPs in South Africa & Thailand



Note: Simple slopes of $COPs_t$ for each $country_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E2.5. Influence of COPs in the UK & the US

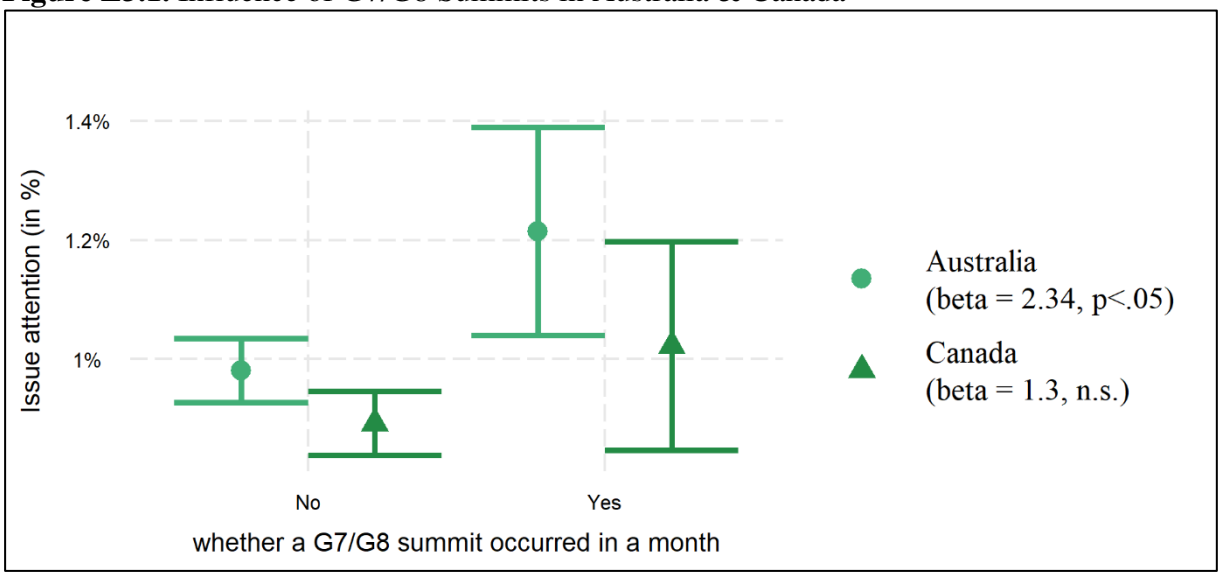


Note: Simple slopes of $COPs_t$ for each $country_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

E3. Influence of Focusing Events across Countries (RQ3): G7/G8 summits

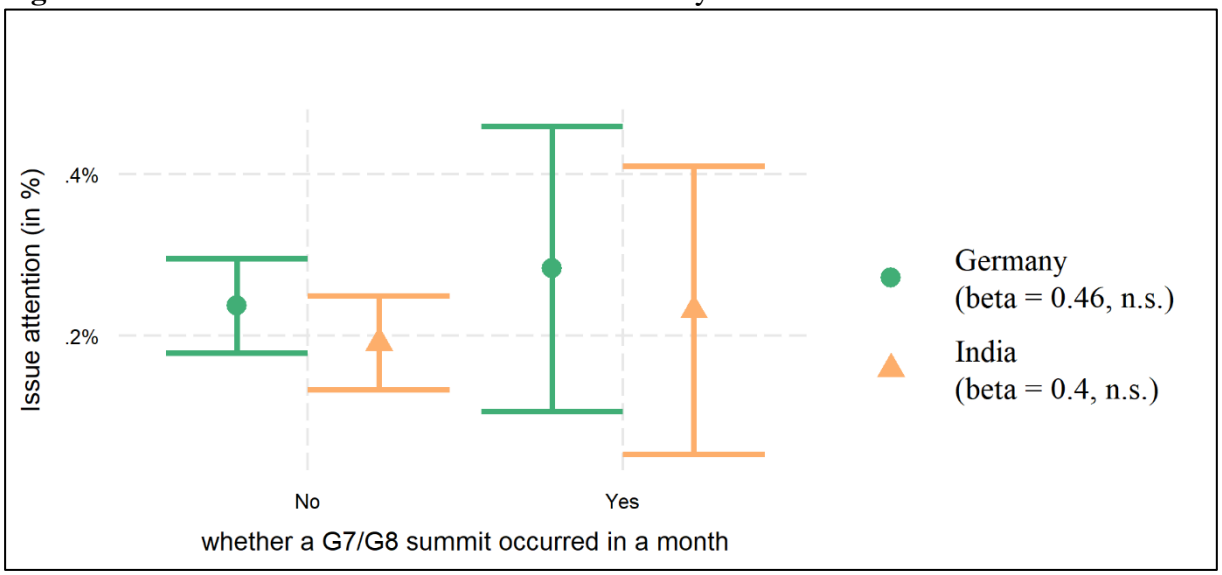
Next, we tested whether G7/G8 summits were associated with peaks in issue attention in some countries but not in others. To do so, we included an interaction between country dummies and *G7/G8 Summits*$_t$. **In short, we found a consistent positive effect of G7/G8 summits on issue attention in Australia.** Figures E3.1–E3.5 visualize the corresponding effects and report the result of each Johnson-Neyman (J-N) test, which indicates whether the simple slope for each country represents a consistent effect or not. If the J-N test is significant, this indicates a consistent effect of G7/G8 summits on issue attention within the specific country (p<.05), otherwise there is no consistent effect (n.s.). In all figures, countries from the Global North are depicted in green while countries from the Global South are depicted in orange.

Figure E3.1. Influence of G7/G8 Summits in Australia & Canada



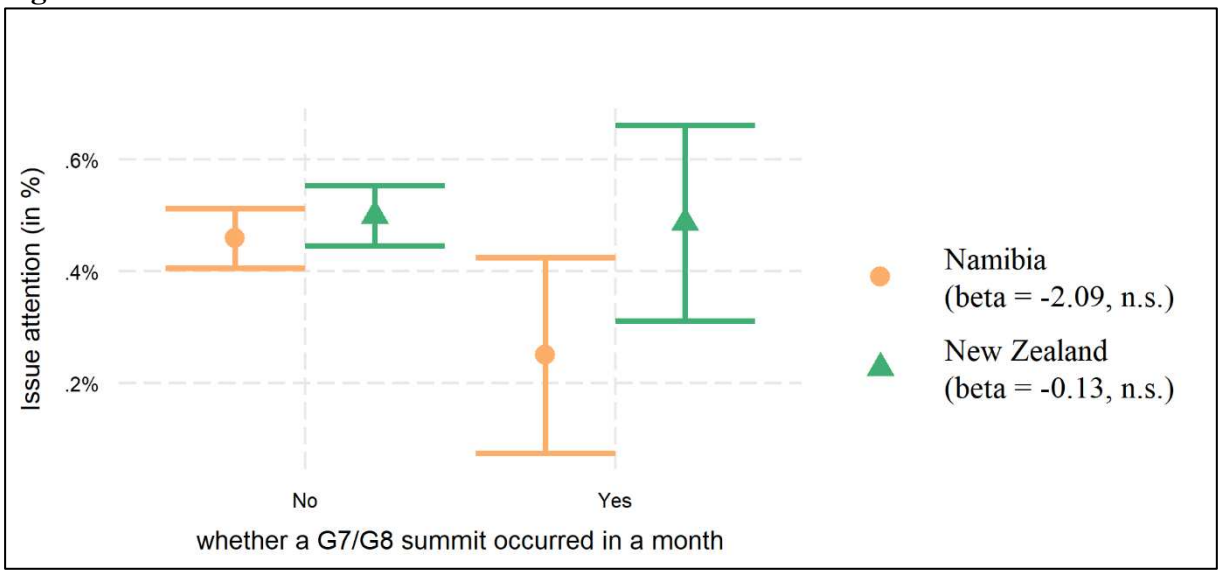
Note: Simple slopes of G7/G8 Summits$_t$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E3.2. Influence of G7/G8 Summits in Germany & India



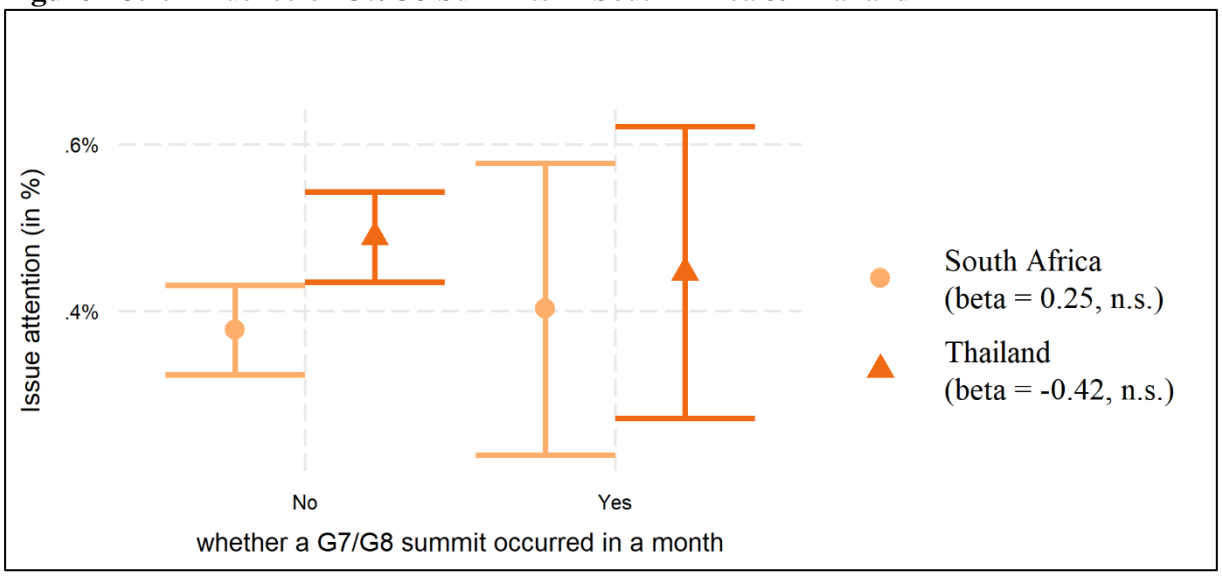
Note: Simple slopes of G7/G8 Summits$_t$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E3.3. Influence of G7/G8 Summits in Namibia & New Zealand



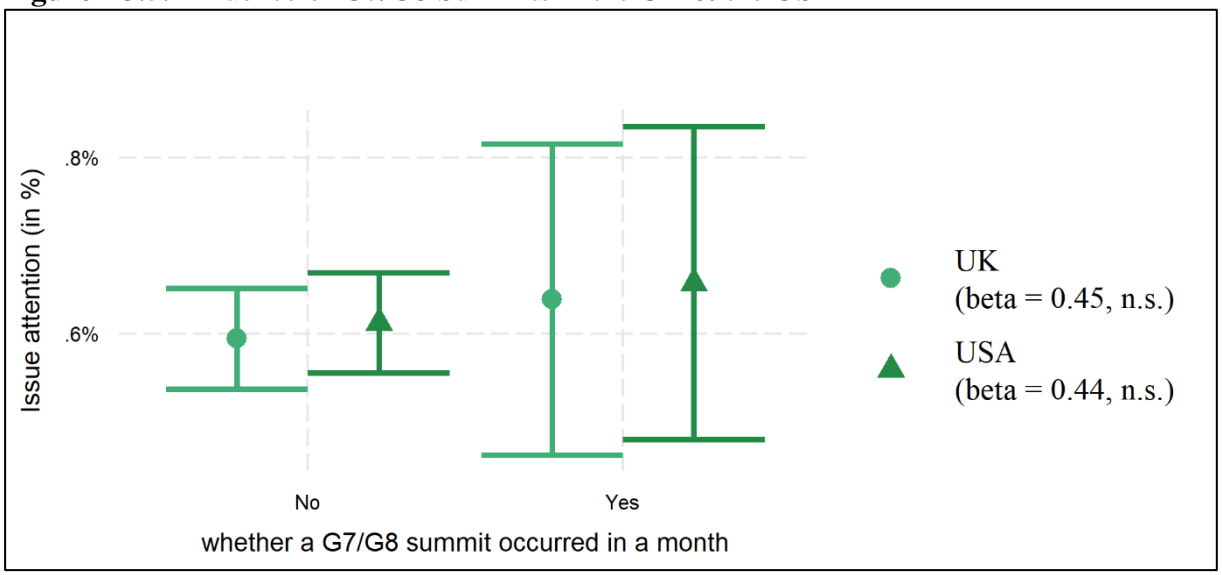
Note: Simple slopes of G7/G8 Summits$_t$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E3.4. Influence of G7/G8 Summits in South Africa & Thailand



Note: Simple slopes of G7/G8 Summits$_t$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E3.5. Influence of G7/G8 Summits in the UK & the US

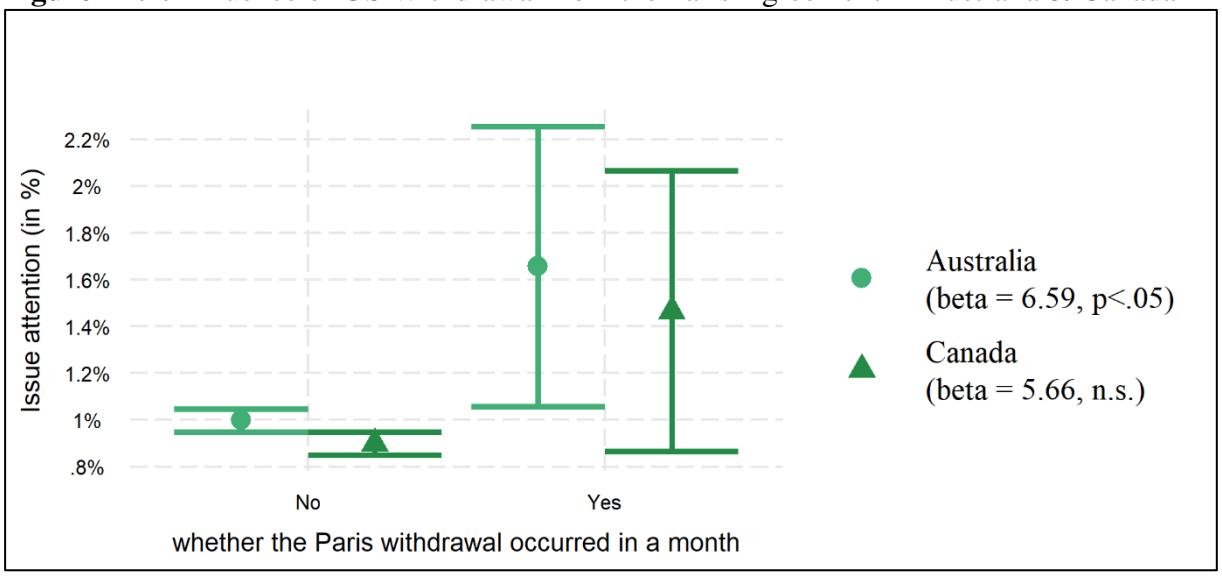


Note: Simple slopes of G7/G8 Summits$_t$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

E4. Influence of Focusing Events across Countries (RQ3): Withdrawal from the Paris Agreement

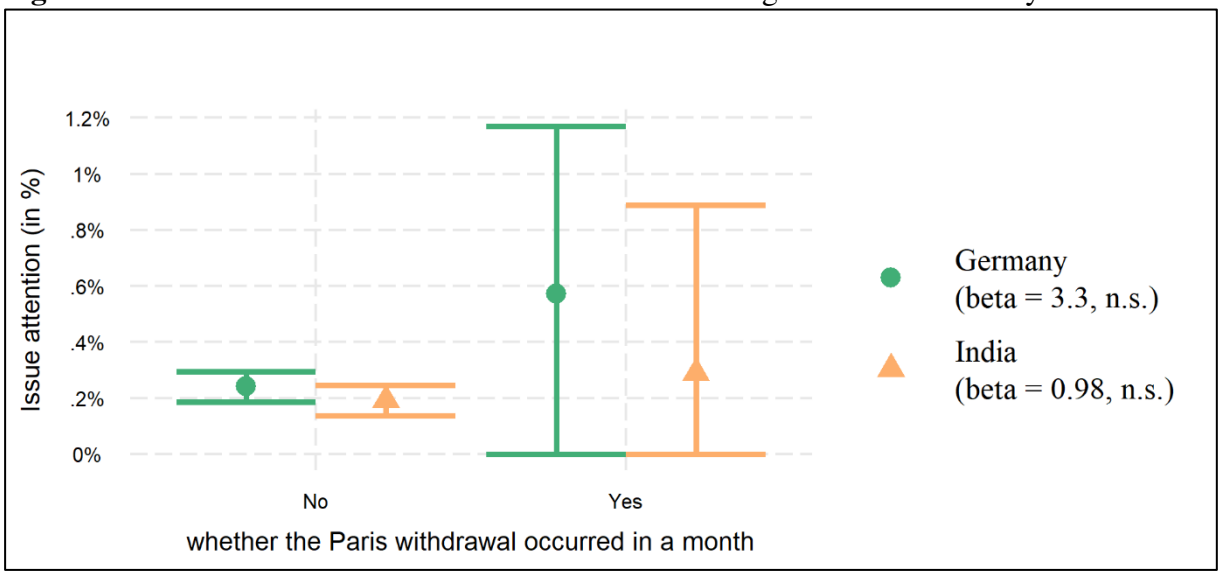
Next, we tested whether the US withdrawal from the Paris agreement was associated with peaks in issue attention in some countries but not in others. To do so, we included an interaction between country dummies and *US Withdrawal from the Paris Agreement*$_t$. **In short, we found a consistent positive effect of the US withdrawal on issue attention in Australia, Namibia, the UK, and the US.** Figures E4.1–E4.5 visualize the corresponding effects and report the result of each Johnson-Neyman (J-N) test, which indicates whether the simple slope for each country represents a consistent effect or not. If the J-N test is significant, this indicates a consistent effect of the event on issue attention within the specific country (p<.05), otherwise there is no consistent effect (n.s.). In all figures, countries from the Global North are depicted in green while countries from the Global South are depicted in orange.

Figure E4.1. Influence of US Withdrawal from the Paris Agreement in Australia & Canada



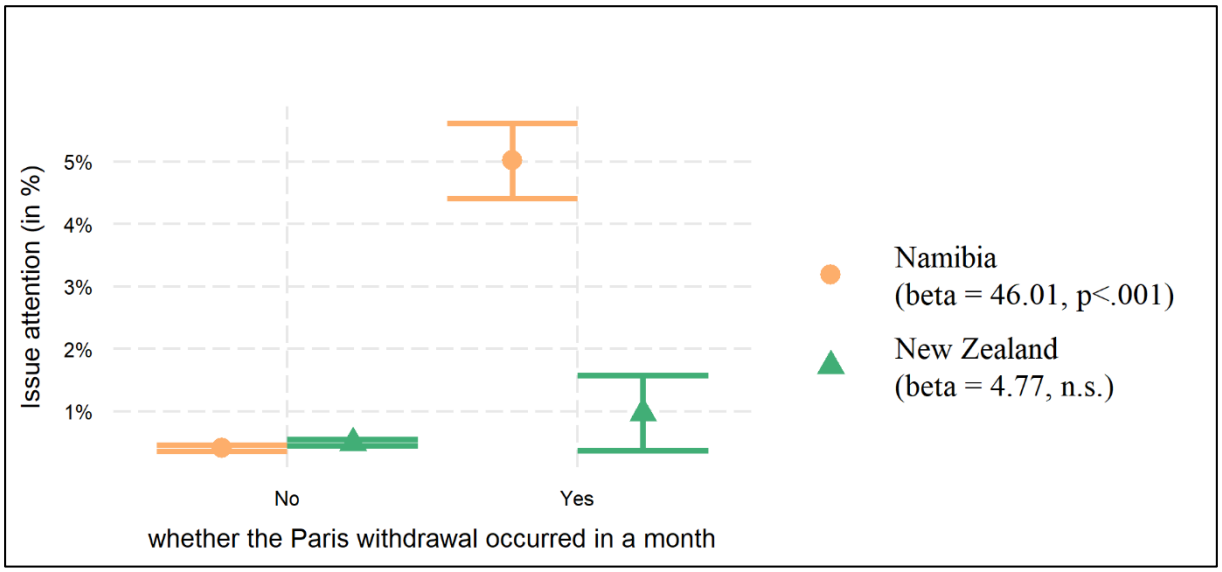
Note: Simple slopes of *Withdrawal from the Paris Agreement*$_t$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E4.2. Influence of US Withdrawal from the Paris Agreement in Germany & India



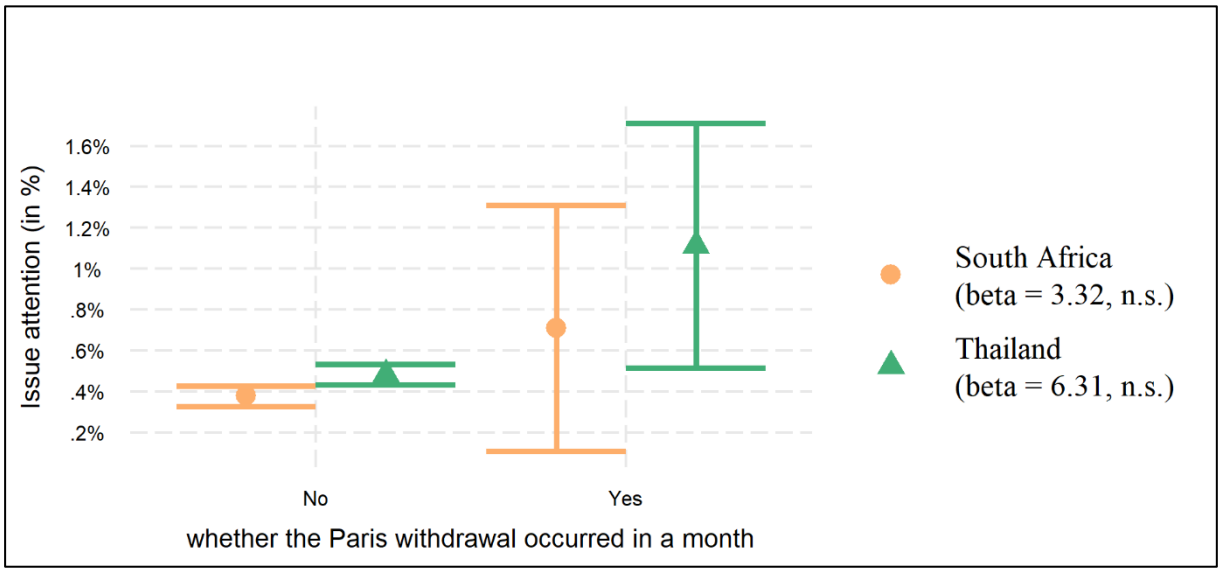
Note: Simple slopes of *Withdrawal from the Paris the Agreement*$_t$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E4.3. Influence of US Withdrawal from the Paris Agreement in Namibia & New Zealand



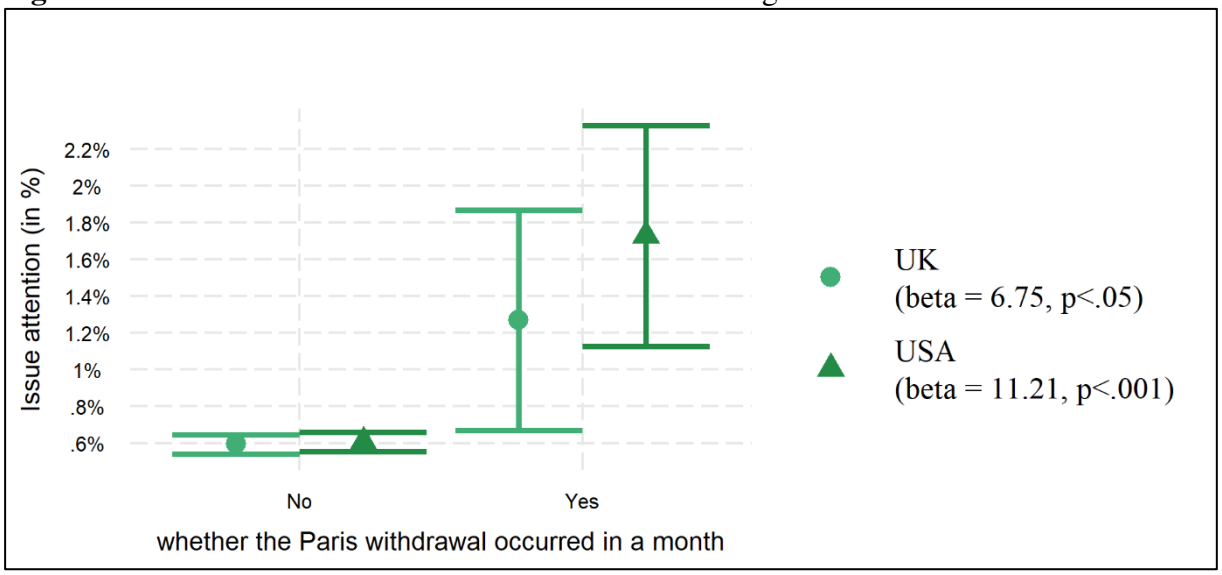
Note: Simple slopes of *Withdrawal from the Paris Agreement*$_t$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E4.4. Influence of US Withdrawal from the Paris Agreement in South Africa & Thailand



Note: Simple slopes of *Withdrawal from the Paris Agreement*$_t$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E4.5. Influence of US Withdrawal from the Paris Agreement in the UK & the US

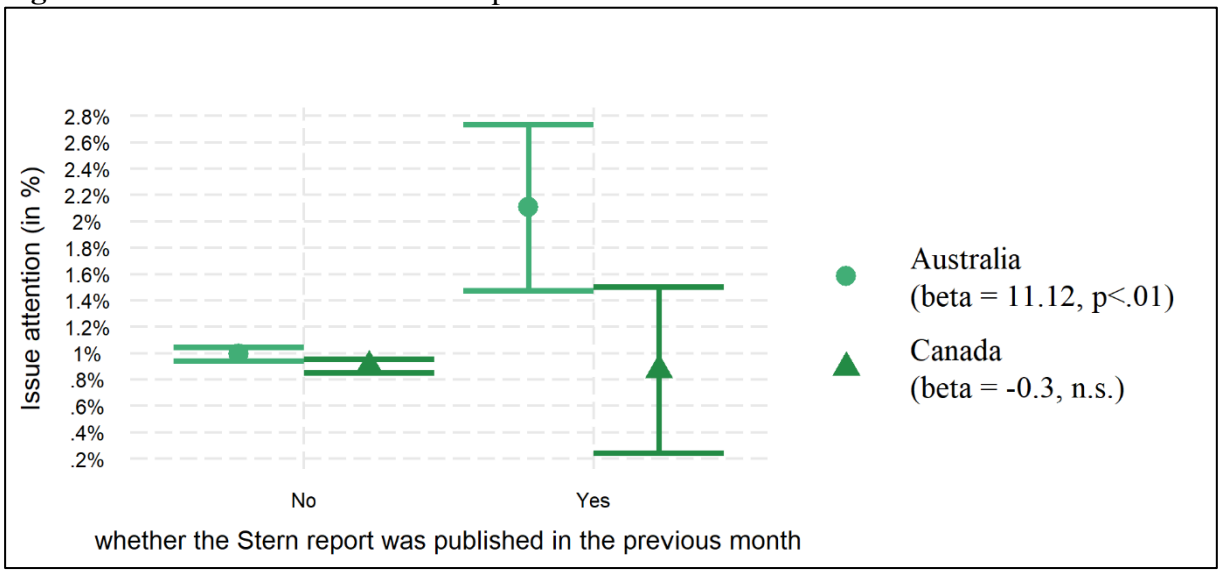


Note: Simple slopes of *Withdrawal from the Paris Agreement*$_t$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

E5. Influence of Focusing Events across Countries (RQ3): Stern Report

Next, we tested whether the Stern Report was associated with peaks in issue attention in some countries but not in others. To do so, we included an interaction between country dummies and *Stern Report*$_{t-1}$. **In short, we found a consistent positive effect of the Stern report on issue attention in Australia and New Zealand.** Figures E5.1–E5.5 visualize the corresponding effects and report the result of each Johnson-Neyman (J-N) test, which indicates whether the simple slope for each country represents a consistent effect or not. If the J-N test is significant, this indicates a consistent effect of the Stern Report on issue attention within the specific country (p<.05), otherwise there is no consistent effect (n.s.). In all figures, countries from the Global North are depicted in green while countries from the Global South are depicted in orange.

Figure E5.1 Influence of the Stern Report in Australia & Canada

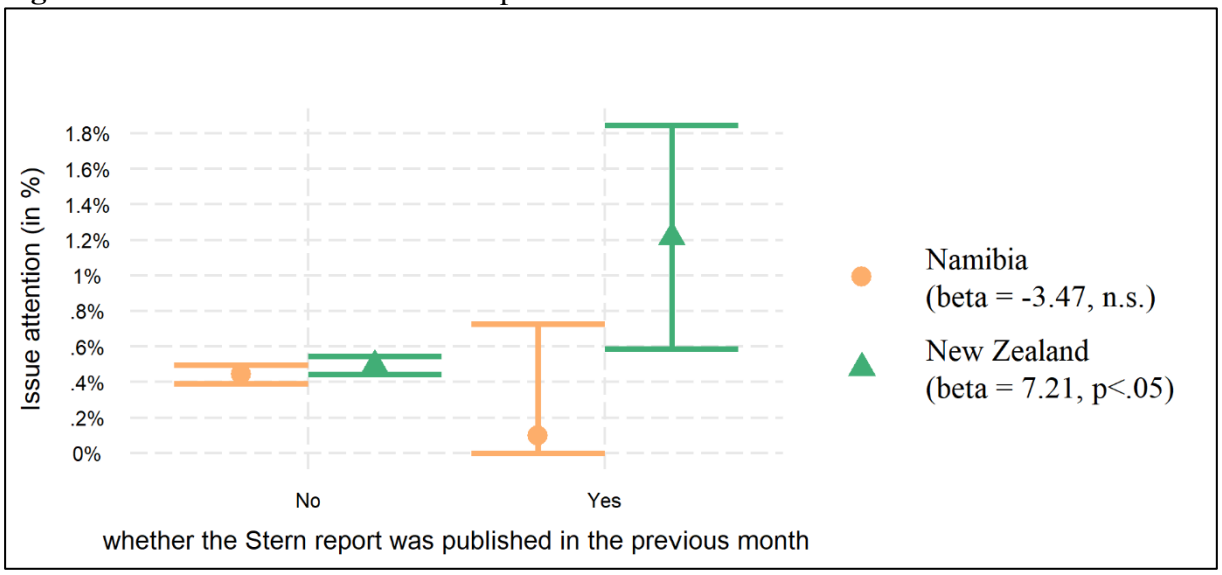


Note: Simple slopes of *Stern Report*$_{t-1}$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E5.2. Influence of the Stern Report in Germany & India

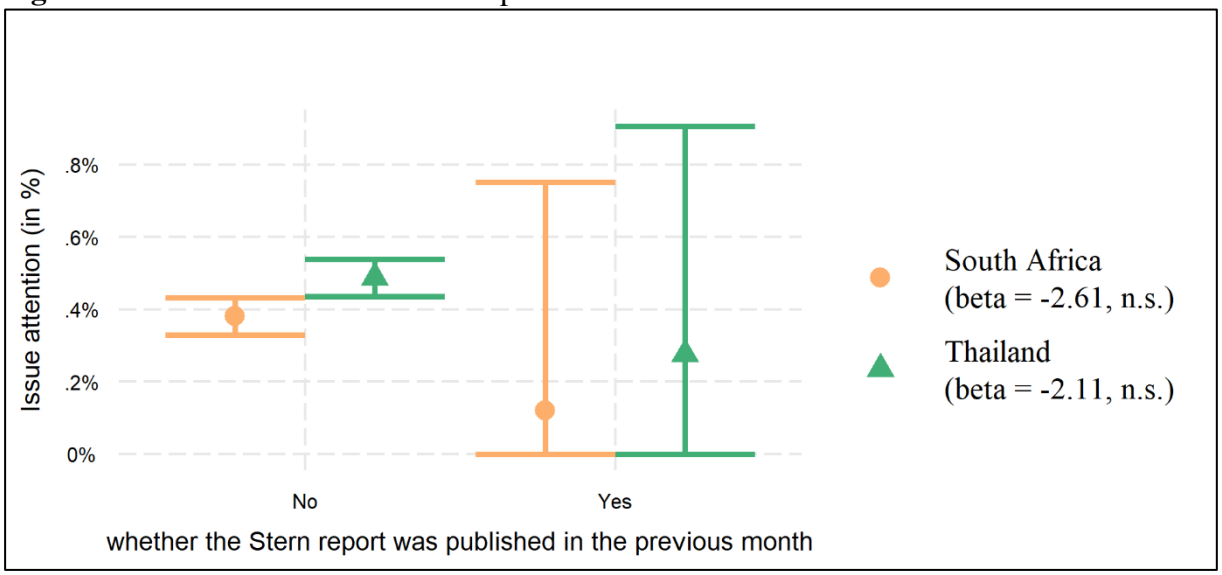
Note: Simple slopes of *Stern Report*$_{t-1}$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E5.3. Influence of the Stern Report in Namibia & New Zealand



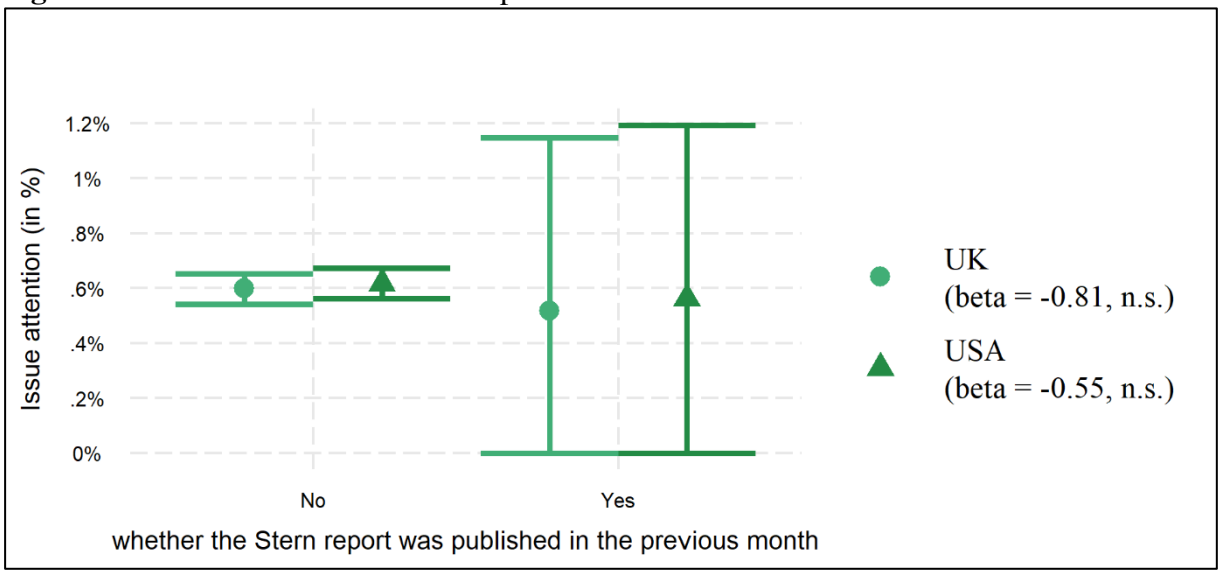
Note: Simple slopes of *Stern Report*$_{t-1}$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E5.4. Influence of the Stern Report in South Africa & Thailand



Note: Simple slopes of *Stern Report*$_{t-1}$ each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E5.5. Influence of the Stern Report in the UK & the US

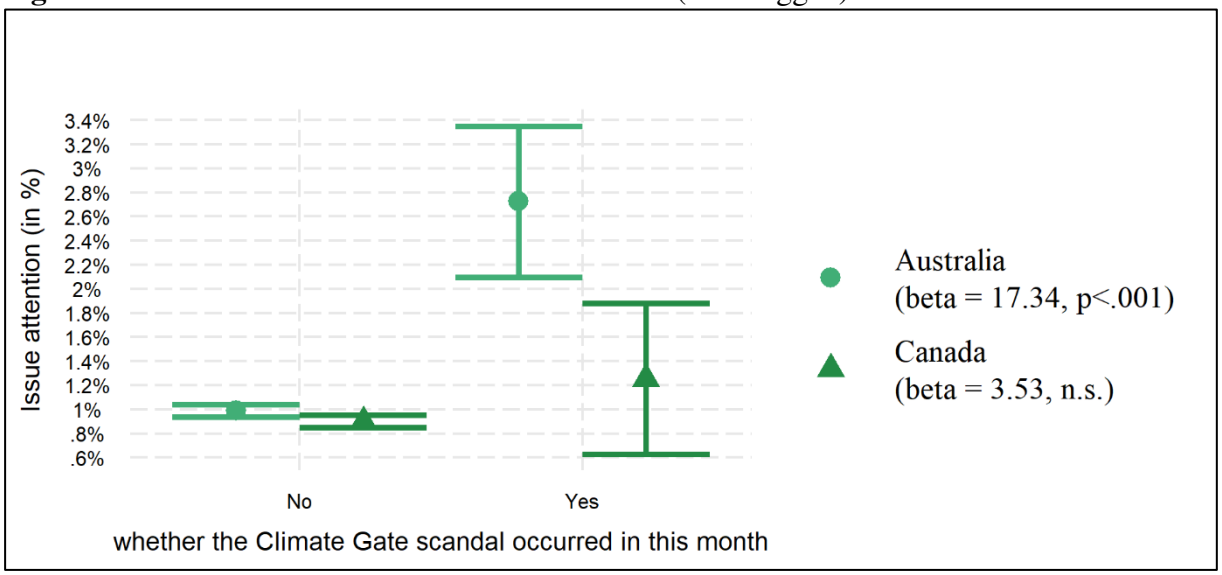


Note: Simple slopes of *Stern Report*$_{t-1}$ for each country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

E6. Influence of Focusing Events across Countries (RQ3): Climate Gate

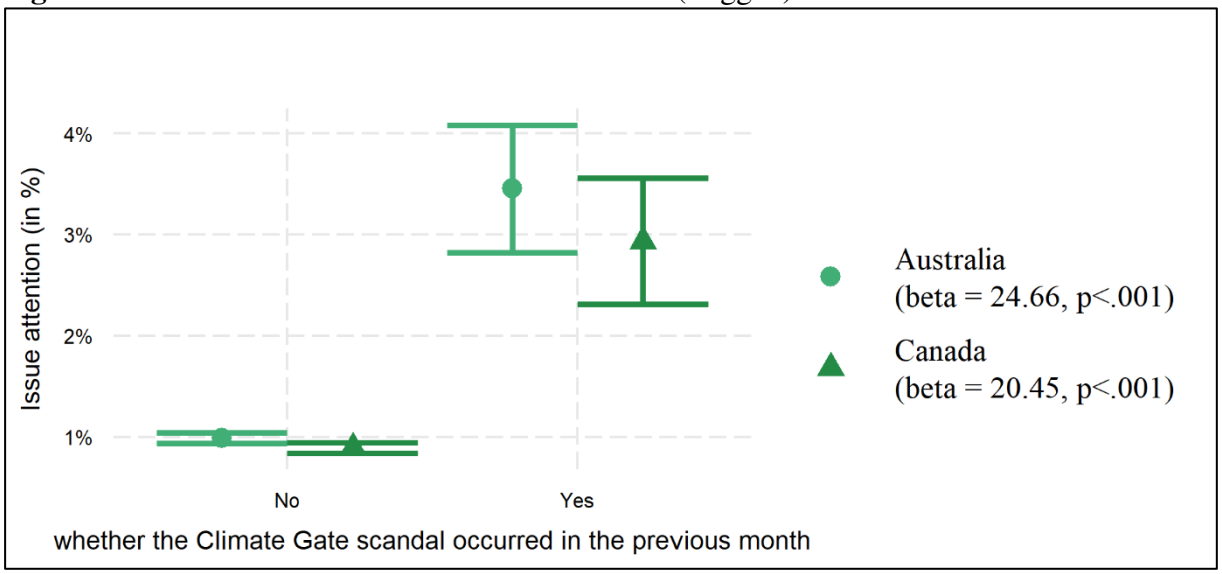
Next, we tested whether the Climate Gate was associated with peaks in issue attention in some countries but not in others. To do so, we included an interaction between country dummies and *Climate Gate*$_t$ and *Climate Gate*$_{t-1}$ (in separate models). **In short, we found a consistent positive effect of the Climate Gate scandal on issue attention in Australia, Canada, Namibia, South Africa, and Thailand.** Figures E6.1–E6.5 visualize the corresponding effects and report the result of each Johnson-Neyman (J-N) test, which indicates whether the simple slope for each country represents a consistent effect or not. If the J-N test is significant, this indicates a consistent effect of the Climate Gate scandal (either in the same month or a lagged effect due to the scandal in the previous month) on issue attention within the specific country (p<.05), otherwise there is no consistent effect (n.s.). In all figures, countries from the Global North are depicted in green while countries from the Global South are depicted in orange.

Figure E6.1. Influence of the Climate Gate Scandal (Not Lagged) in Australia & Canada



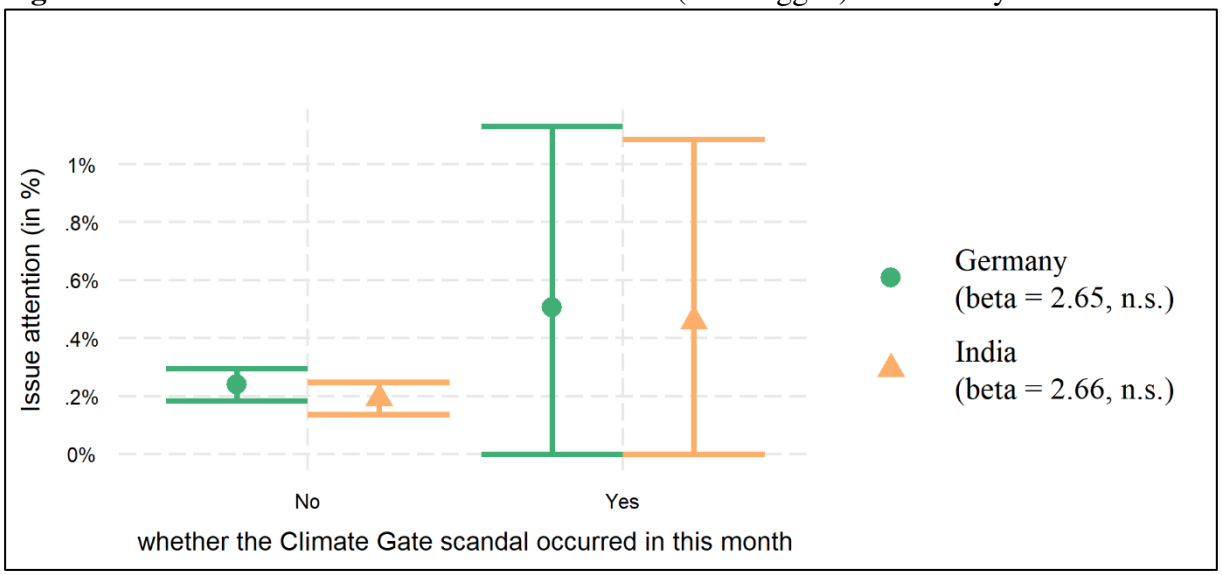
Note: Simple slopes of *Climate Gate*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E6.2. Influence of the Climate Gate Scandal (Lagged) in Australia & Canada



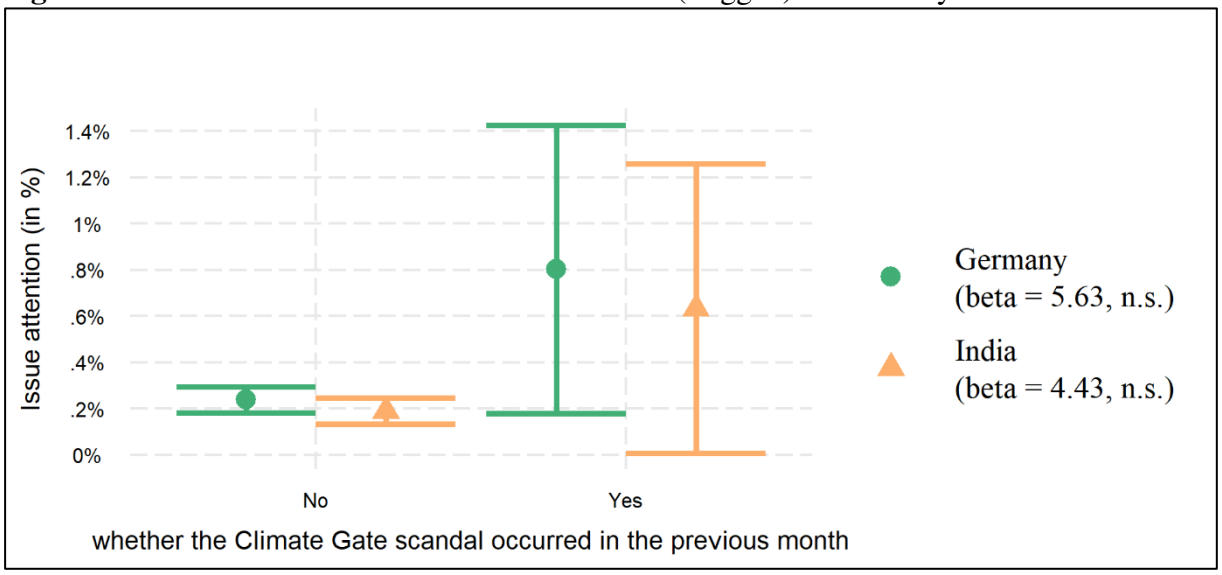
Note: Simple slopes of *Climate Gate*$_{t-1}$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E6.3. Influence of the Climate Gate Scandal (Not Lagged) in Germany & India



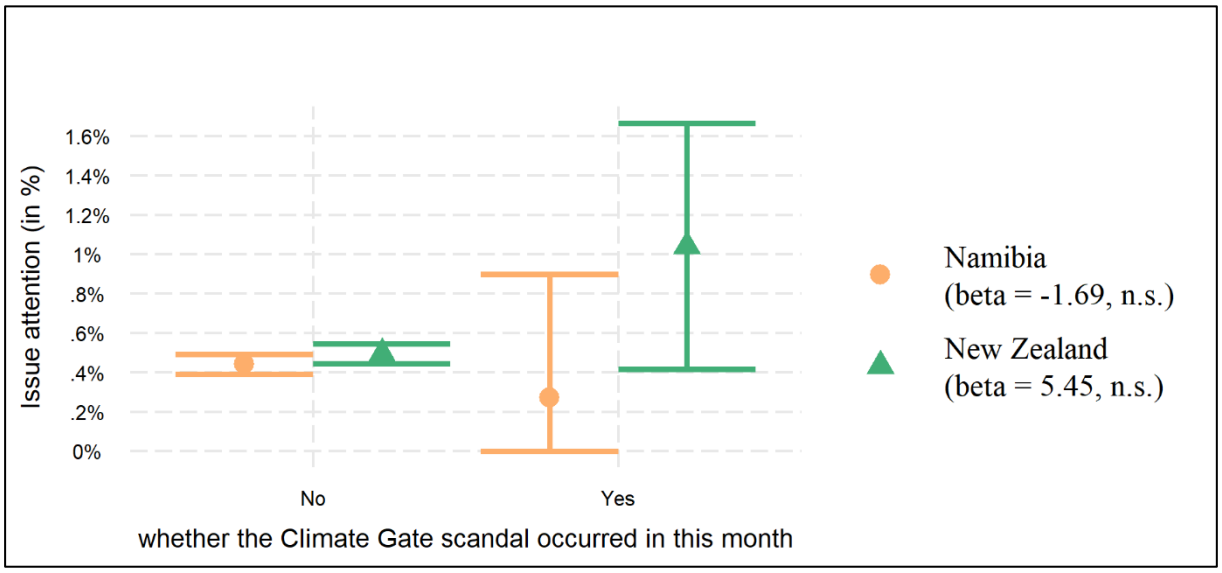
Note: Simple slopes of *Climate Gate*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E6.4. Influence of the Climate Gate Scandal (Lagged) in Germany & India



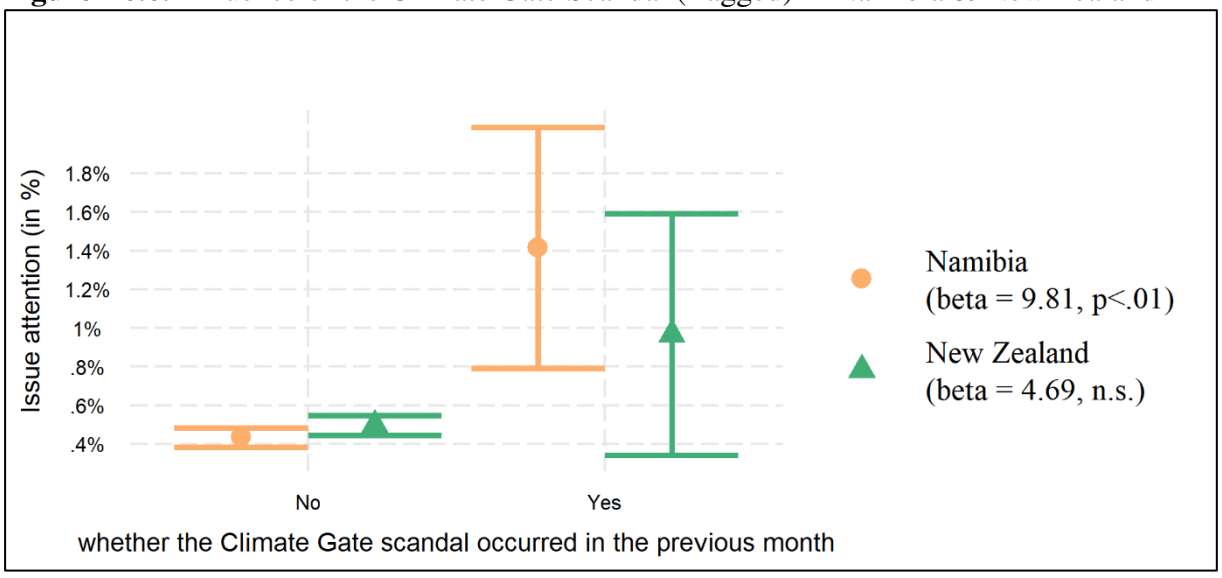
Note: Simple slopes of *Climate Gate*$_{t-1}$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E6.5. Influence of the Climate Gate Scandal (Not Lagged) in Namibia & New Zealand



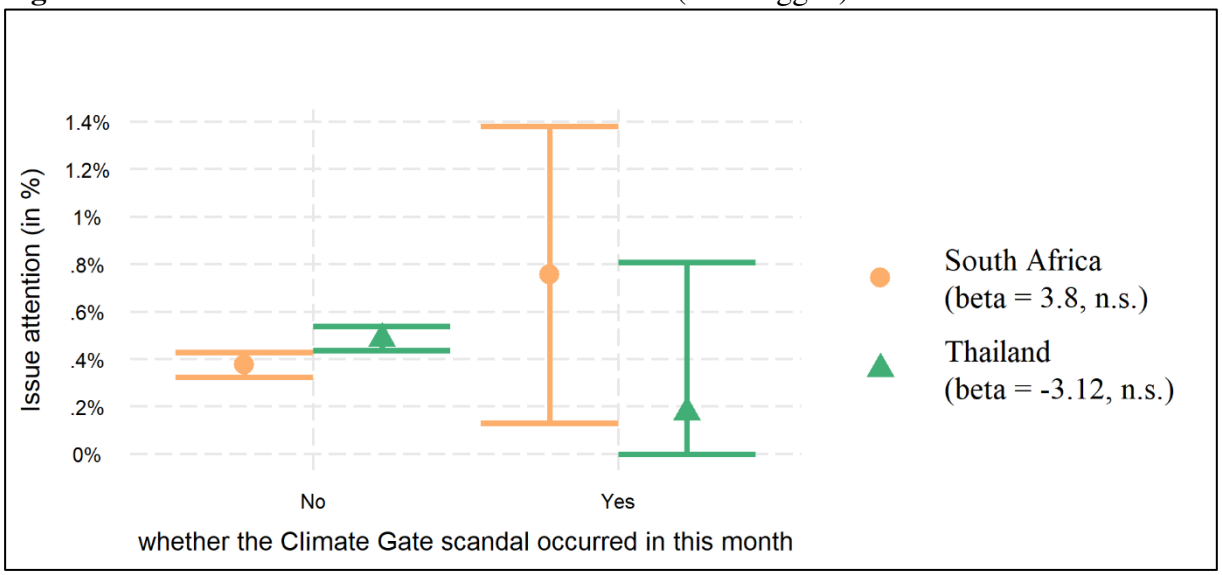
Note: Simple slopes of *Climate Gate*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E6.6. Influence of the Climate Gate Scandal (Lagged) in Namibia & New Zealand



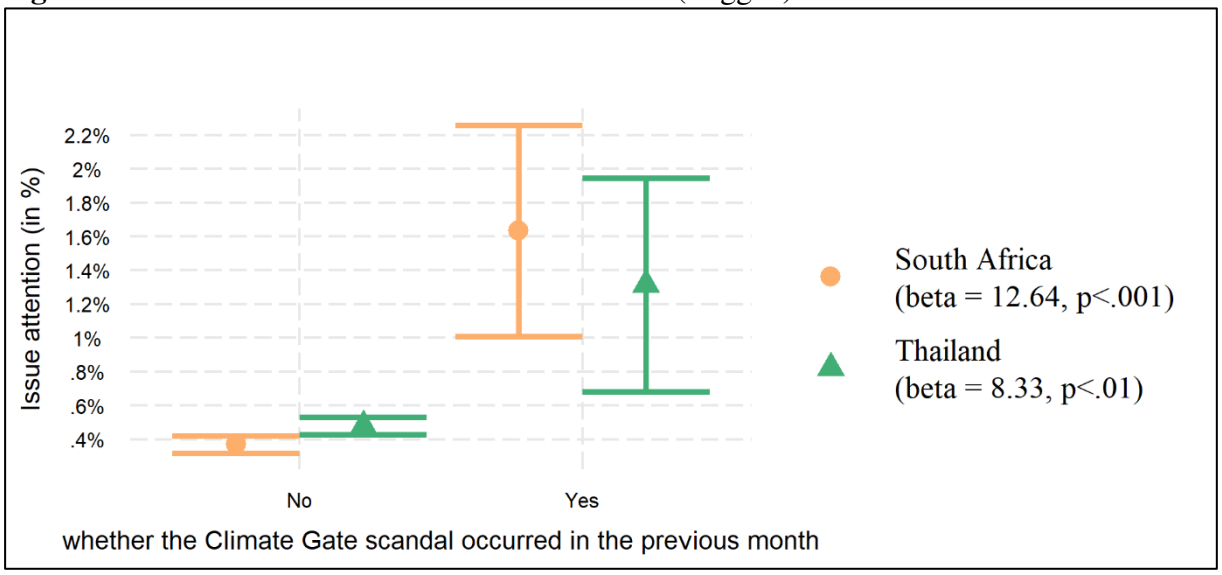
Note: Simple slopes of *Climate Gate*$_{t-1}$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E6.7. Influence of the Climate Gate Scandal (Not Lagged) in South Africa & Thailand



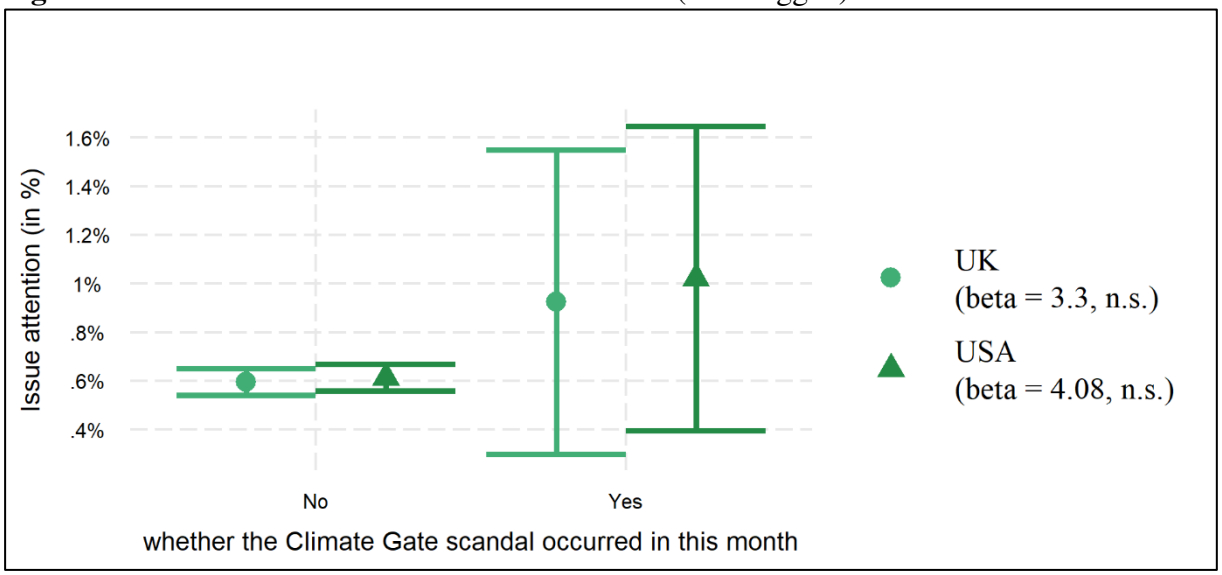
Note: Simple slopes of *Climate Gate*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E6.8. Influence of the Climate Gate Scandal (Lagged) in South Africa & Thailand



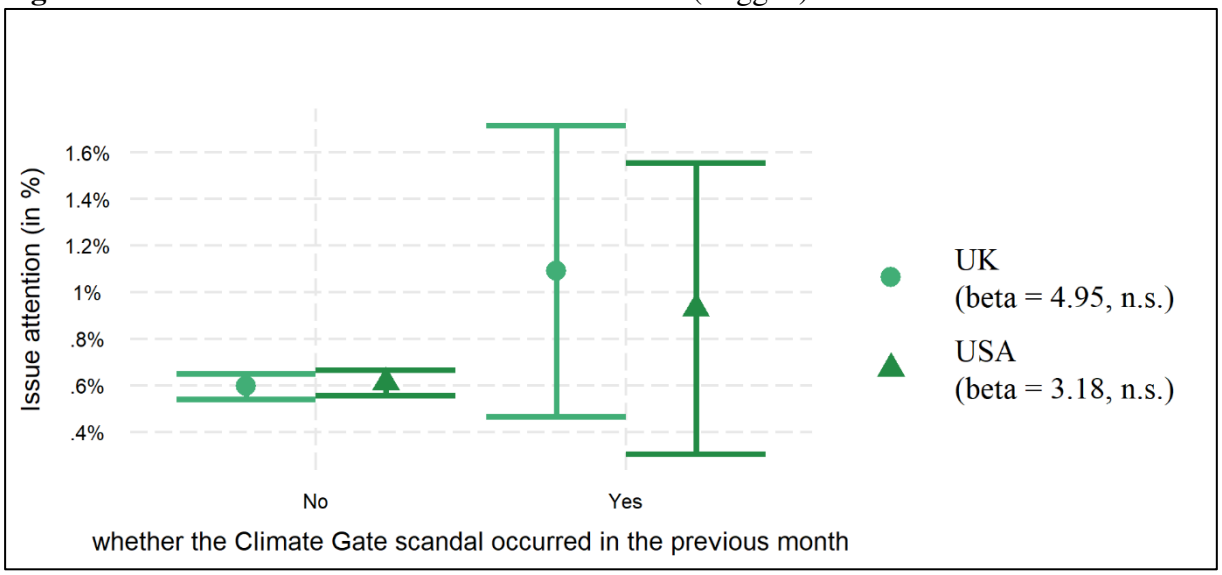
Note: Simple slopes of *Climate Gate*$_{t-1}$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E6.9. Influence of the Climate Gate Scandal (Not Lagged) in the UK & the US



Note: Simple slopes of *Climate Gate*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E6.10. Influence of the Climate Gate Scandal (Lagged) in the UK & the US

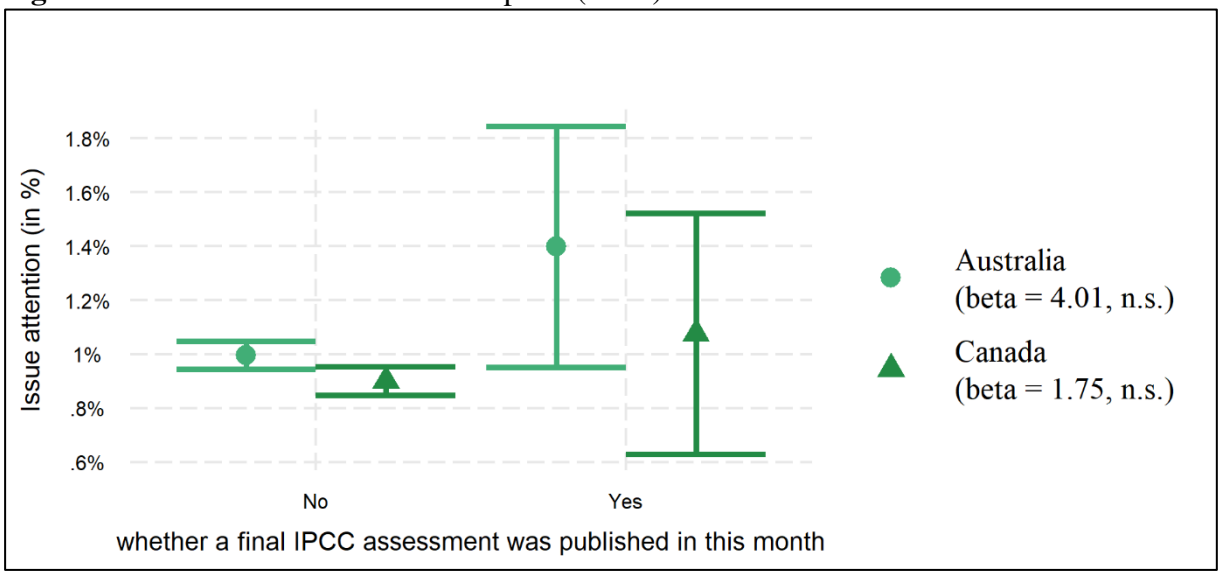


Note: Simple slopes of *Climate Gate*$_{t-1}$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

E7. Influence of Focusing Events across Countries (RQ3): IPCC reports

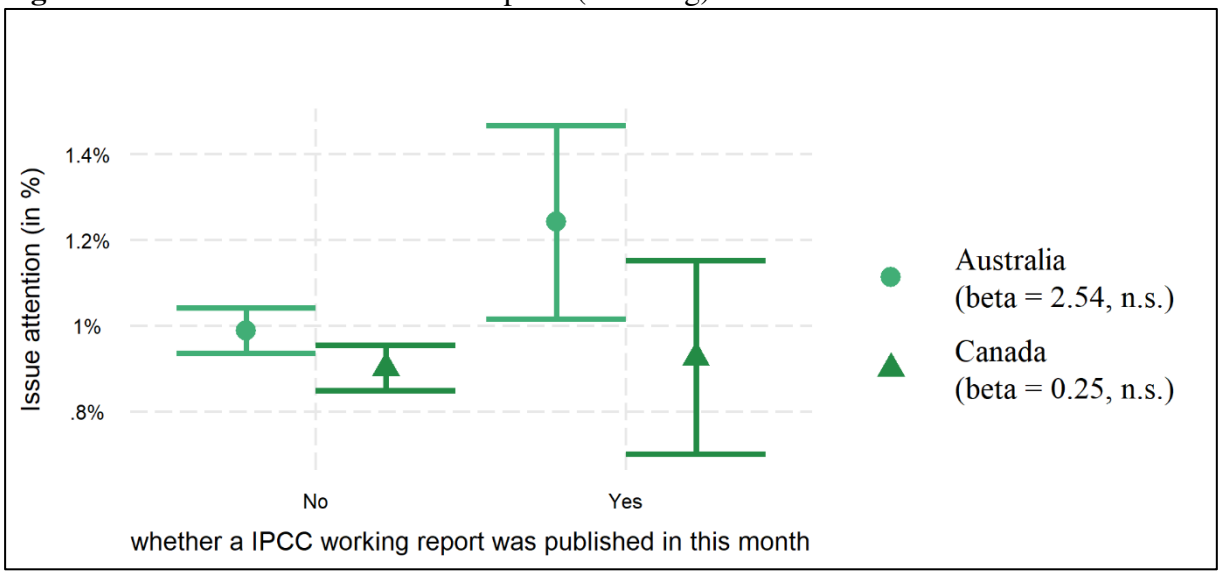
Next, we tested whether the IPCC reports were associated with peaks in issue attention in some countries but not in others. To do so, we included an interaction between country dummies and *IPCC Reports (Final)*$_t$ as well as country dummies and *IPCC Reports (Working)*$_t$ (in separate models). **In short, we did not find a consistent effect of IPCCs reports on issue attention in any country.** Figures E7.1–E7.10 visualize the corresponding effects and report the result of each Johnson-Neyman (J-N) test, which indicates whether the simple slope for each country represents a consistent effect or not. If the J-N test is significant, this indicates a consistent effect of the respective IPCC report on issue attention within the specific country (p<.05), otherwise there is no consistent effect (n.s.). In all figures, countries from the Global North are depicted in green while countries from the Global South are depicted in orange.

Figure E7.1. Influence of the IPCC Reports (Final) in Australia & Canada



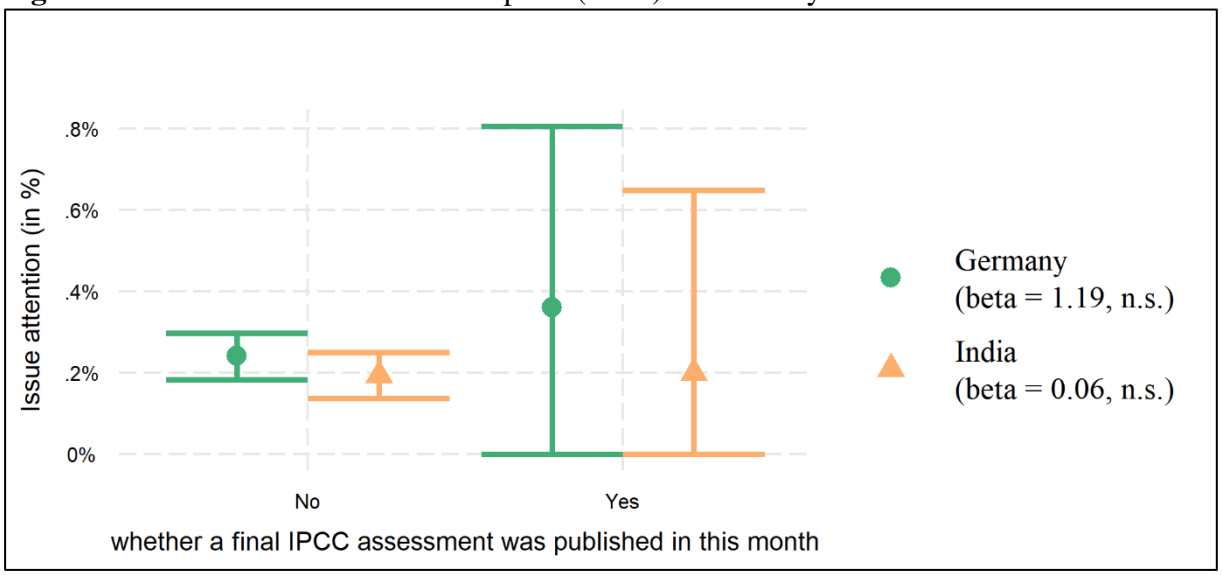
Note: Simple slopes of *IPCC Reports (Final)*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E7.2. Influence of the IPCC Reports (Working) in Australia & Canada



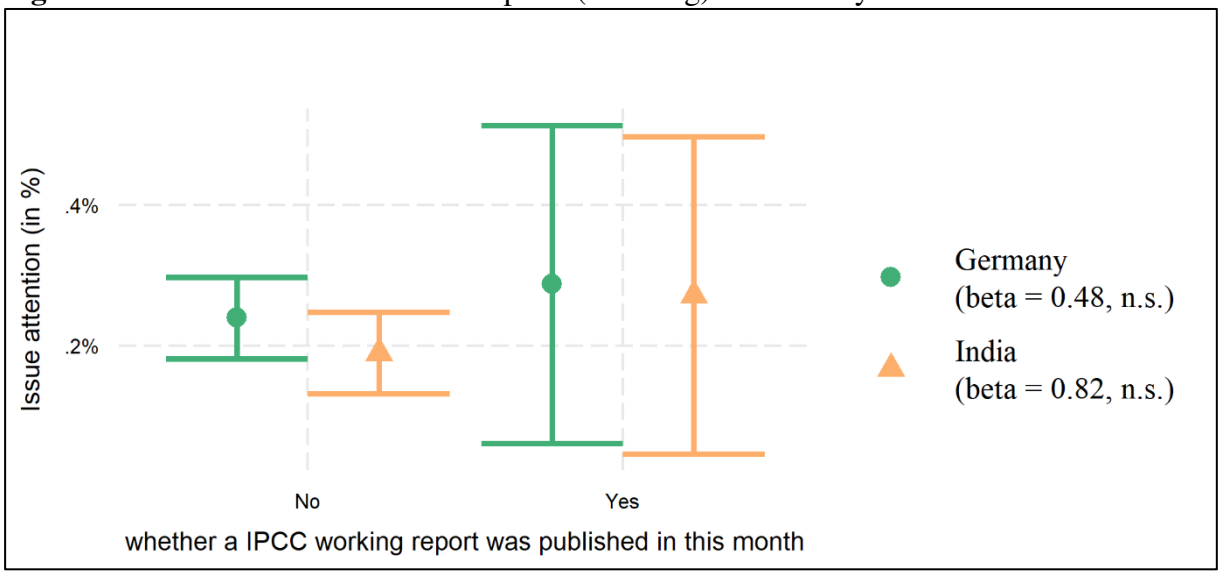
Note: Simple slopes of *IPCC Reports (Working)*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E7.3. Influence of the IPCC Reports (Final) in Germany & India



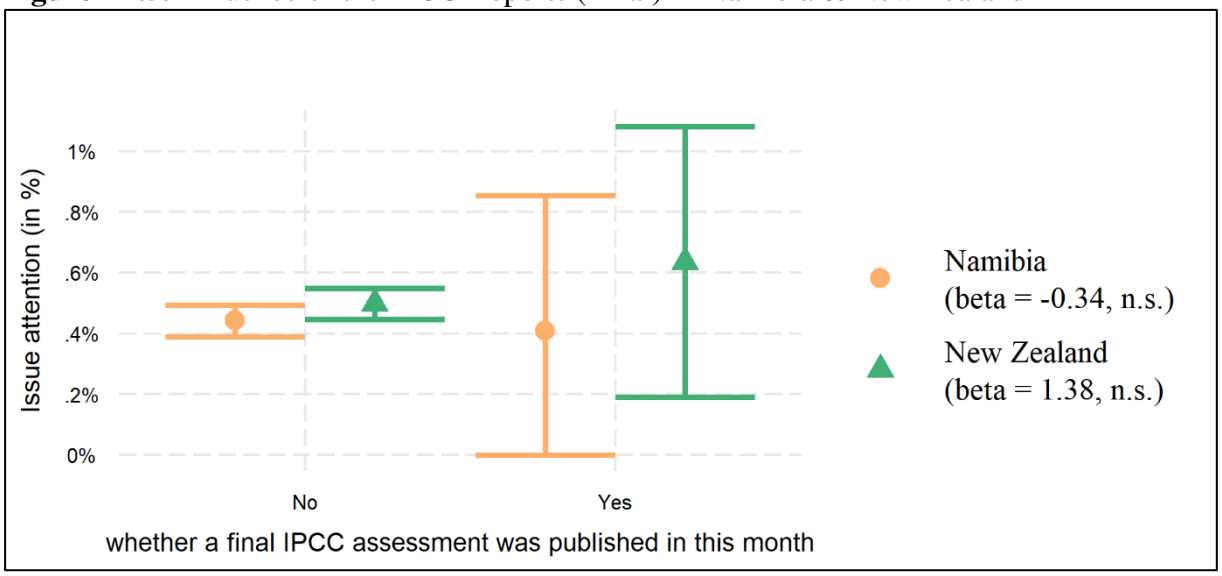
Note: Simple slopes of *IPCC Reports (Final)*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E7.4. Influence of the IPCC Reports (Working) in Germany & India



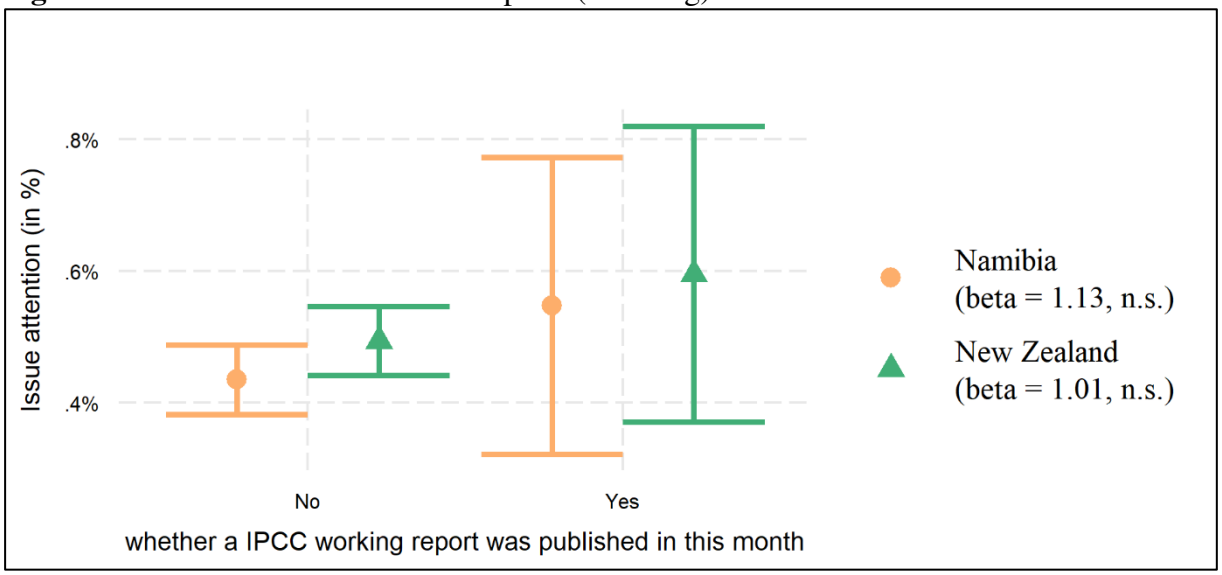
Note: Simple slopes of *IPCC Reports (Working)*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E7.5. Influence of the IPCC Reports (Final) in Namibia & New Zealand



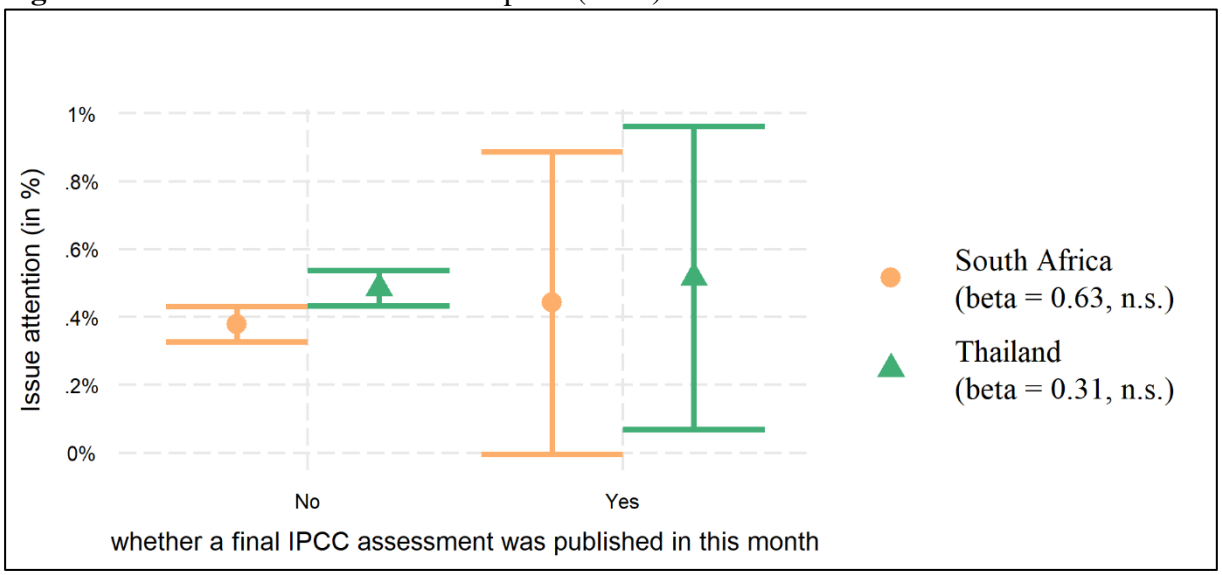
Note: Simple slopes of *IPCC Reports (Final)*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E7.6. Influence of the IPCC Reports (Working) in Namibia & New Zealand



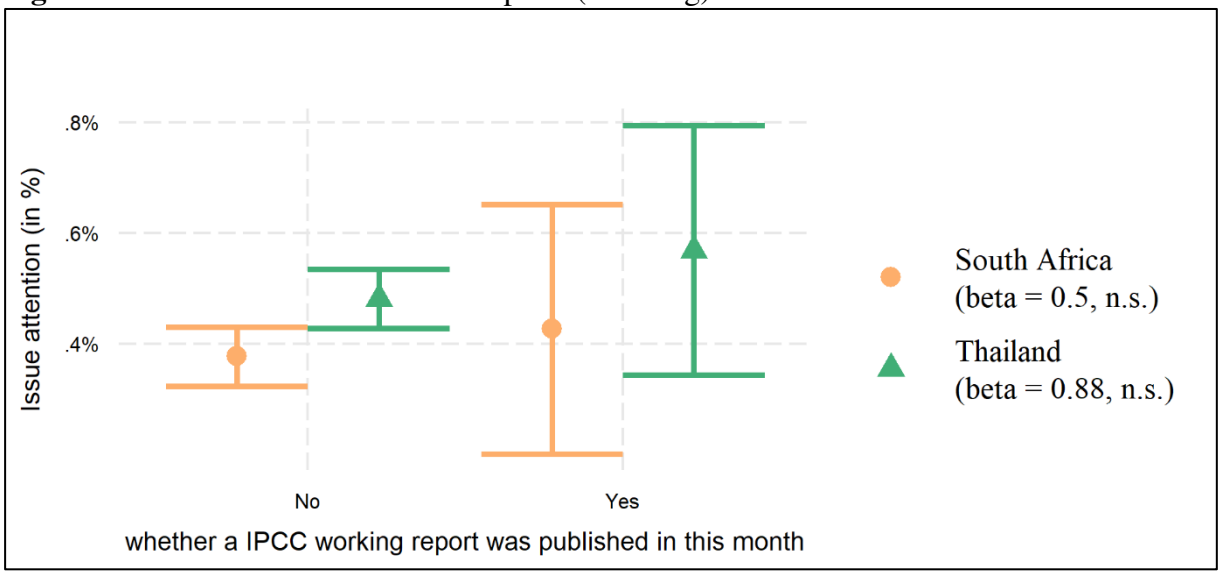
Note: Simple slopes of *IPCC Reports (Working)*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E7.7. Influence of the IPCC Reports (Final) in South Africa & Thailand



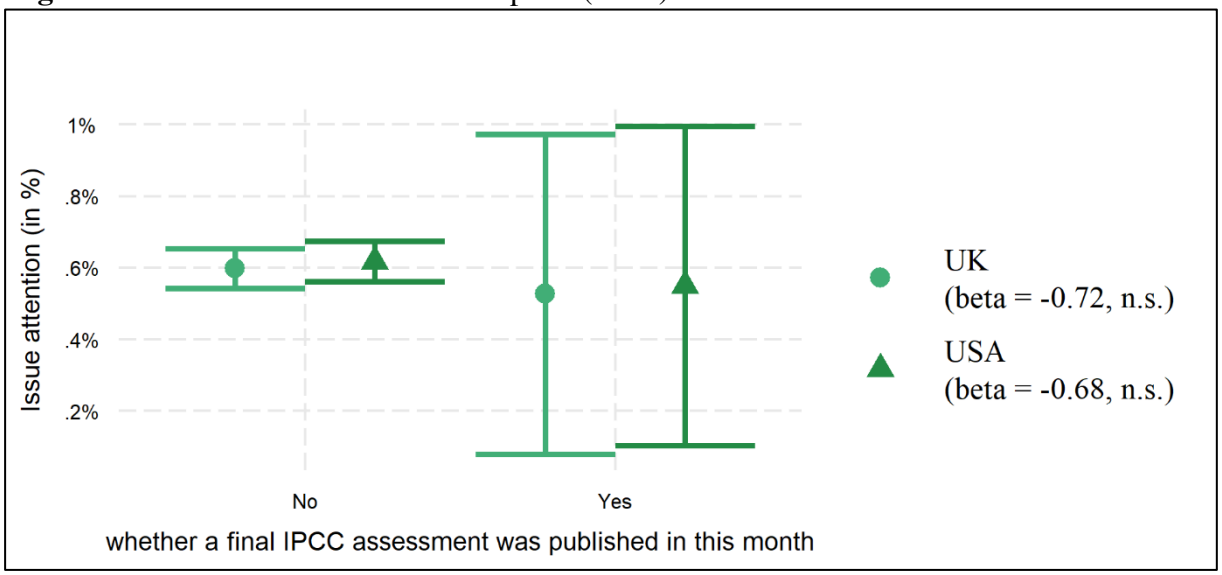
Note: Simple slopes of *IPCC Reports (Final)*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E7.8. Influence of the IPCC Reports (Working) in South Africa & Thailand



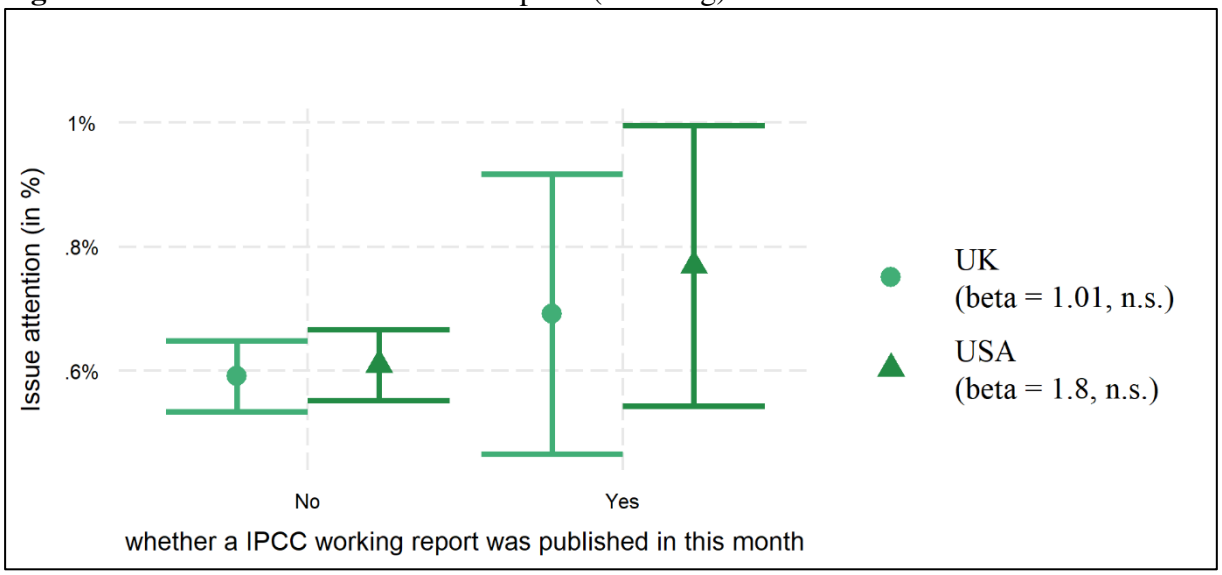
Note: Simple slopes of *IPCC Reports (Working)*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E7.9. Influence of the IPCC Reports (Final) in the UK & the US



Note: Simple slopes of *IPCC Reports (Final)*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E7.10. Influence of the IPCC Reports (Working) in the UK & the US

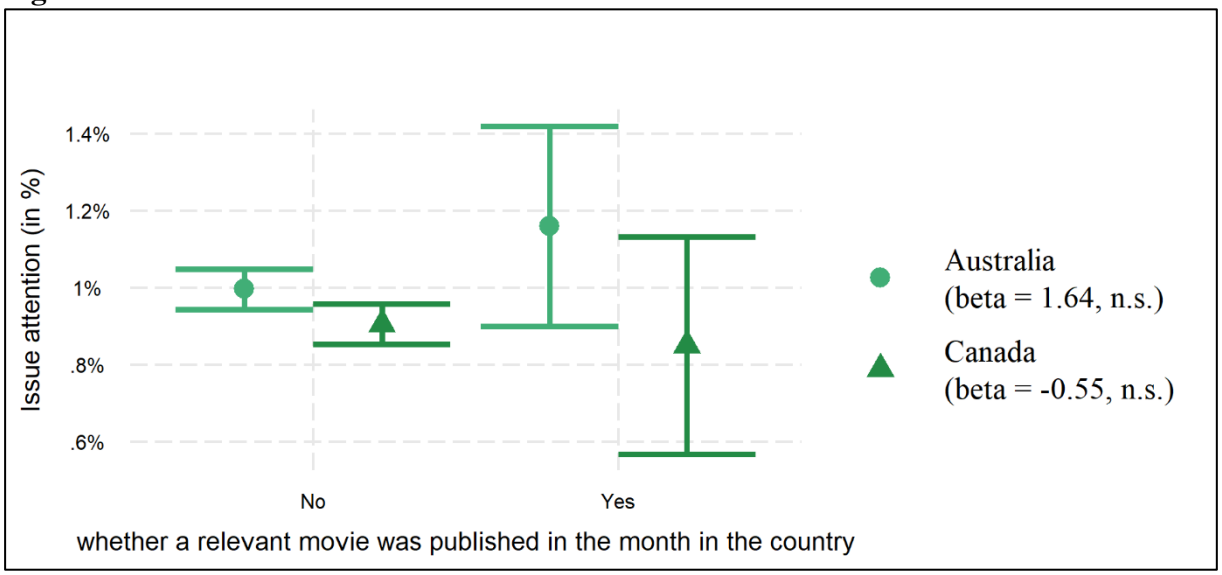


Note: Simple slopes of *IPCC Reports (Working)*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

E8. Influence of Focusing Events across Countries (RQ3): Release of Movies

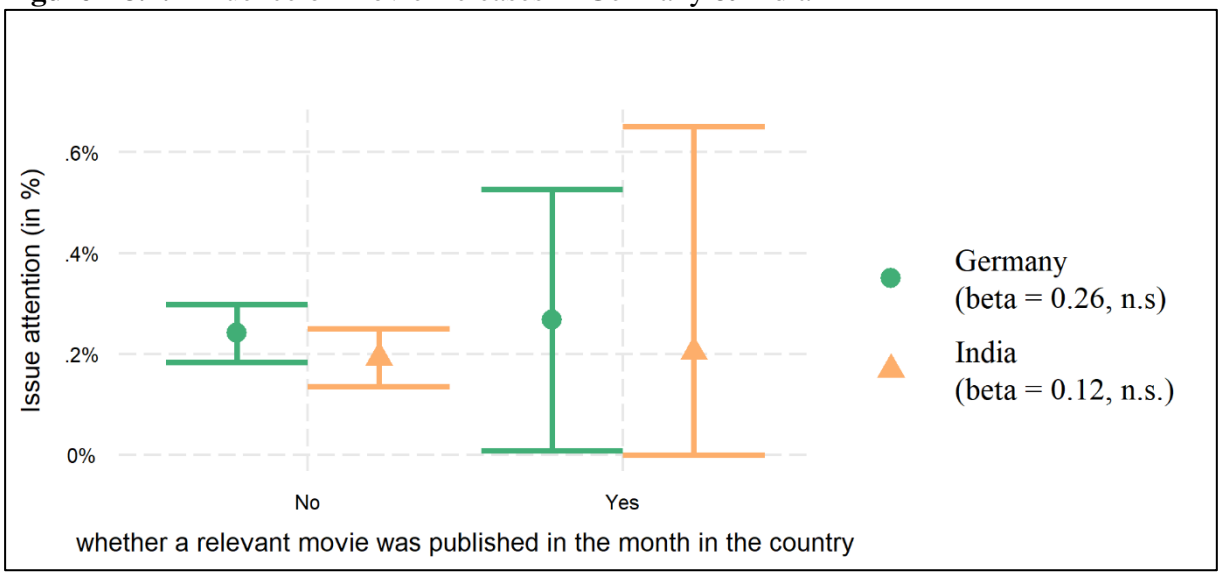
Next, we tested whether the release of climate change related movies in each country was associated with peaks in issue attention in some countries but not in others. To do so, we included an interaction between country dummies and *Release of Movies*$_{t,i}$. **In short, we did not find a consistent effect of movies on issue attention in any country.** Figures E8.1–E8.5 visualize the corresponding effects and report the result of each Johnson-Neyman (J-N) test, which indicates whether the simple slope for each country represents a consistent effect or not. If the J-N test is significant, this indicates a consistent effect of the movies on issue attention within the specific country (p<.05), otherwise there is no consistent effect (n.s.). In all figures, countries from the Global North are depicted in green while countries from the Global South are depicted in orange.

Figure E8.1. Influence of Movie Releases in Australia & Canada



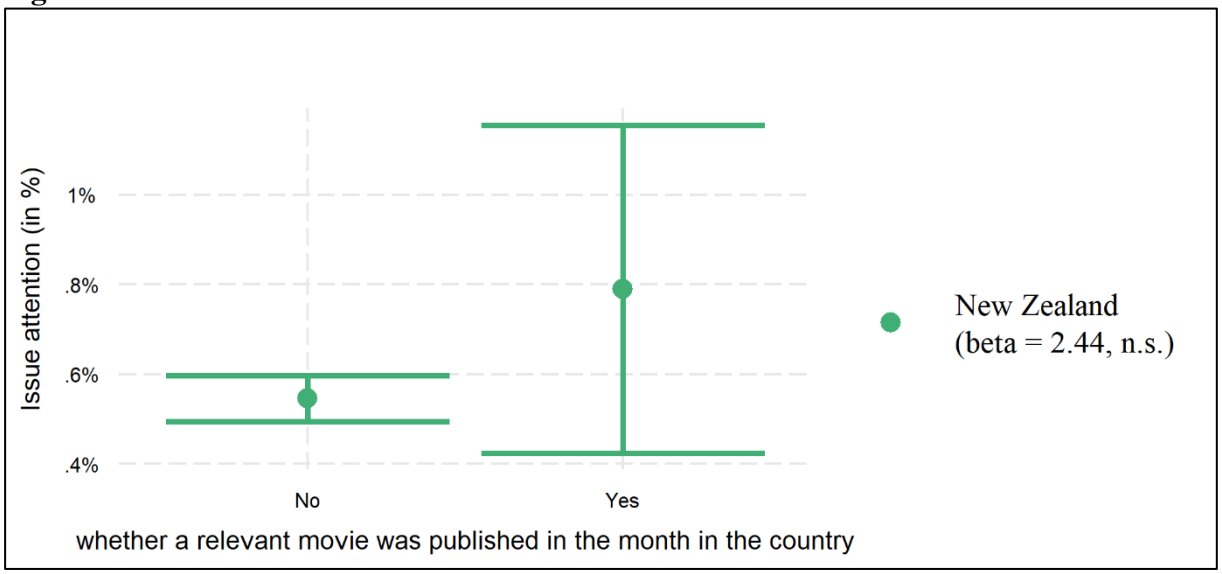
Note: Simple slopes of *Release of Movies*$_{t,i}$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E8.2. Influence of Movie Releases in Germany & India



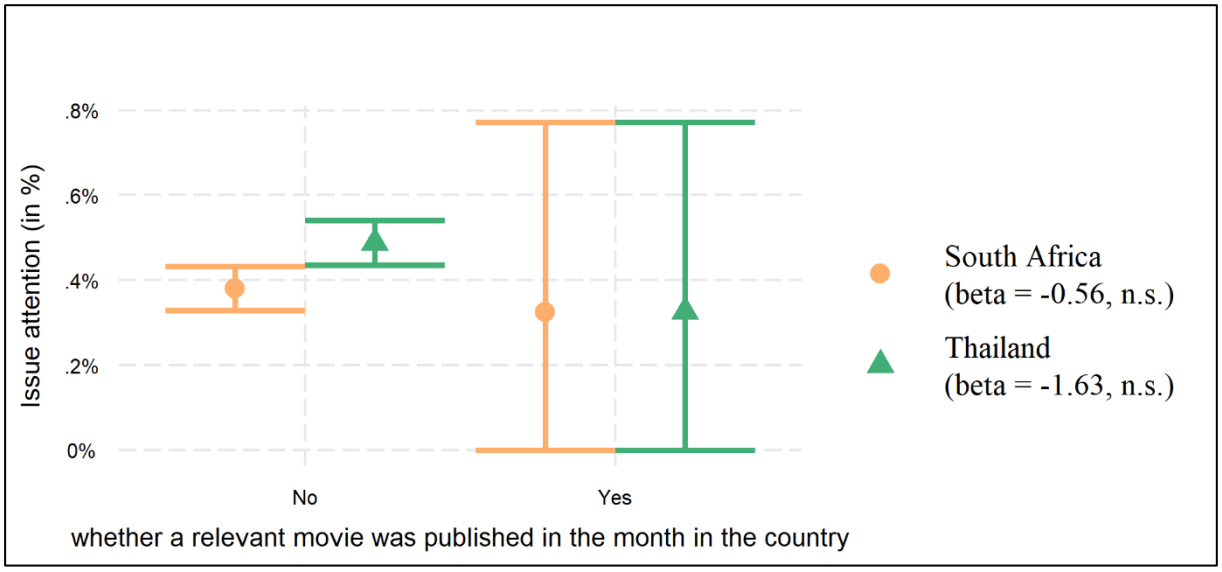
Note: Simple slopes of *Release of Movies*$_{t,i}$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E8.3. Influence of Movie Releases in New Zealand



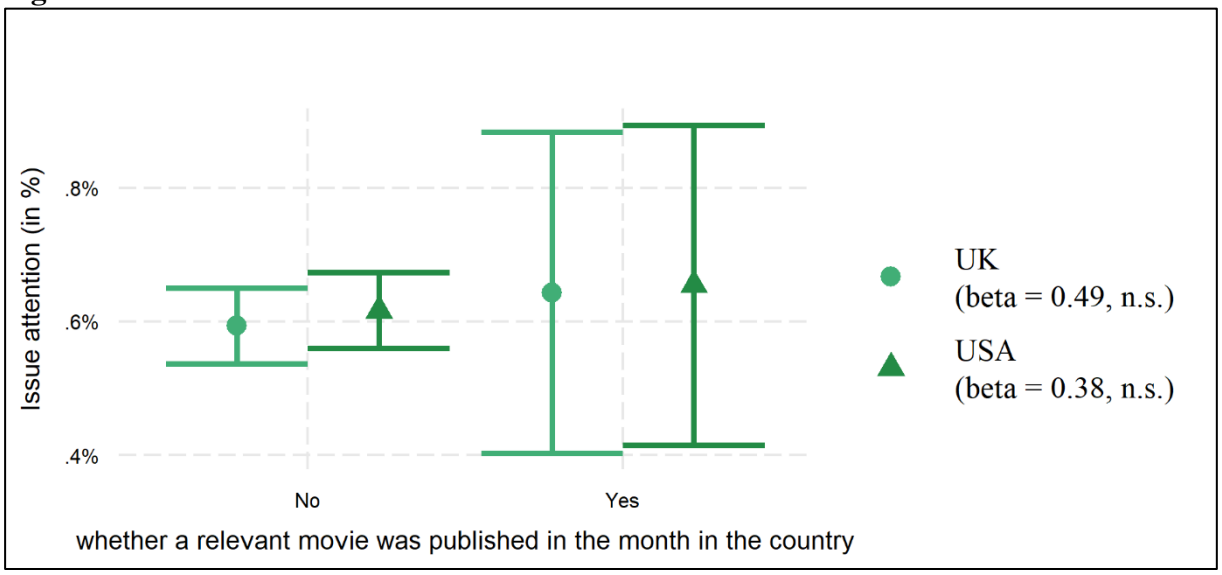
Note: Simple slopes of *Release of Movies*$_{t,i}$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange. Please note that effects for Namibia were not estimated since none of the movies were release there.

Figure E8.4. Influence of Movie Releases in South Africa & Thailand



Note: Simple slopes of *Release of Movies*$_{t,i}$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E8.5 Influence of Movie Releases in the UK & the US

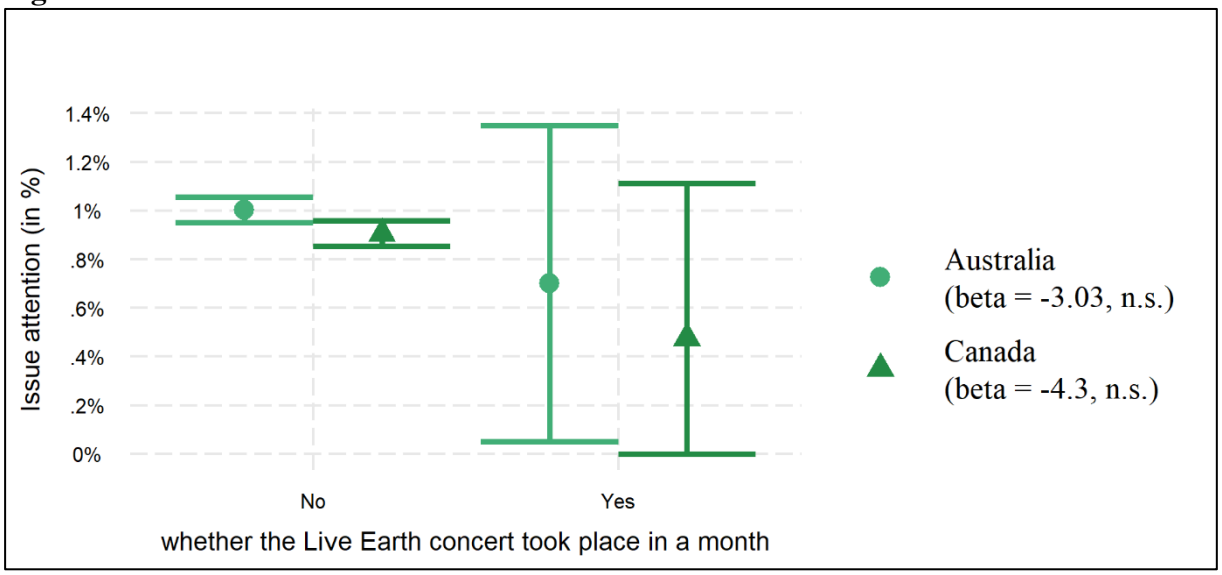


Note: Simple slopes of *Release of Movies*$_{t,i}$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

E9. Influence of Focusing Events across Countries (RQ3): Live Earth Concert

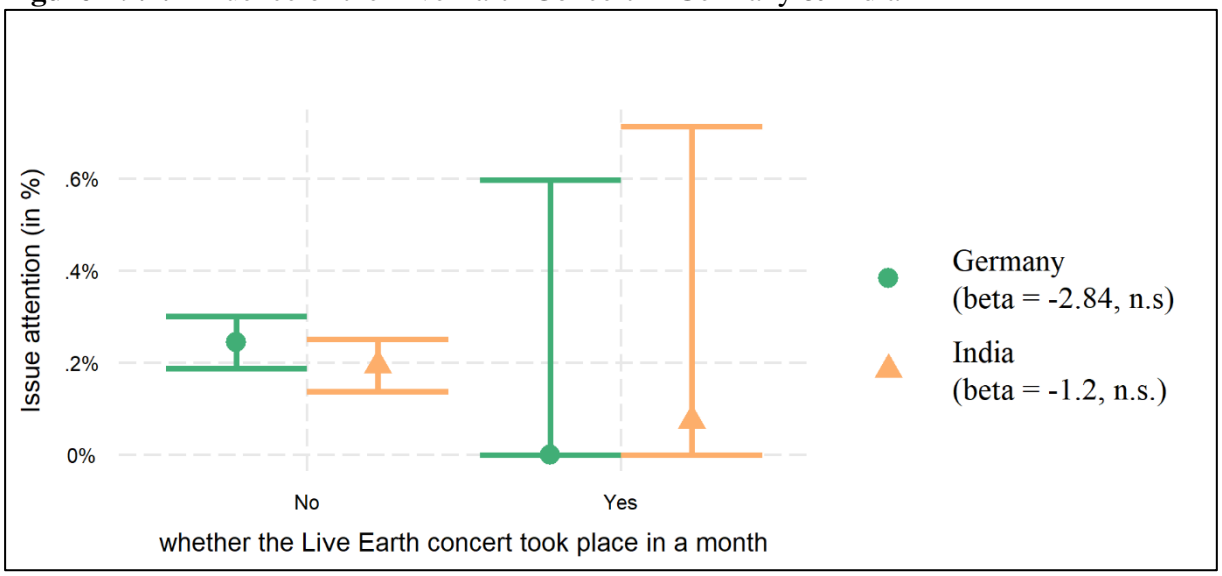
Next, we tested whether the Live Earth Concert was associated with peaks in issue attention in some countries but not in others. To do so, we included an interaction between country dummies and *Live Earth Concert*$_t$. **In short, we did not find a consistent effect of the Live Earth Concert on issue attention in any country.** Figures E9.1–E9.5 visualize the corresponding effects and report the result of each Johnson-Neyman (J-N) test, which indicates whether the simple slope for each country represents a consistent effect or not. If the J-N test is significant, this indicates a consistent effect of the concert on issue attention within the specific country (p<.05), otherwise there is no consistent effect (n.s.). In all figures, countries from the Global North are depicted in green while countries from the Global South are depicted in orange.

Figure E9.1. Influence of the Live Earth Concert in Australia & Canada



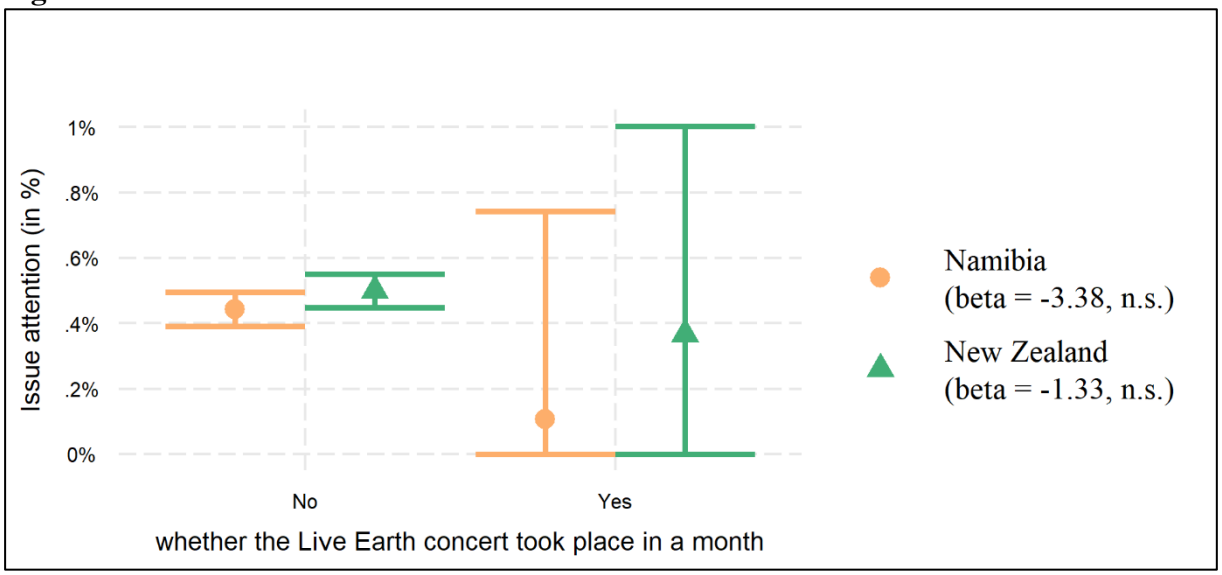
Note: Simple slopes of *Live Earth Concert*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E9.2. Influence of the Live Earth Concert in Germany & India



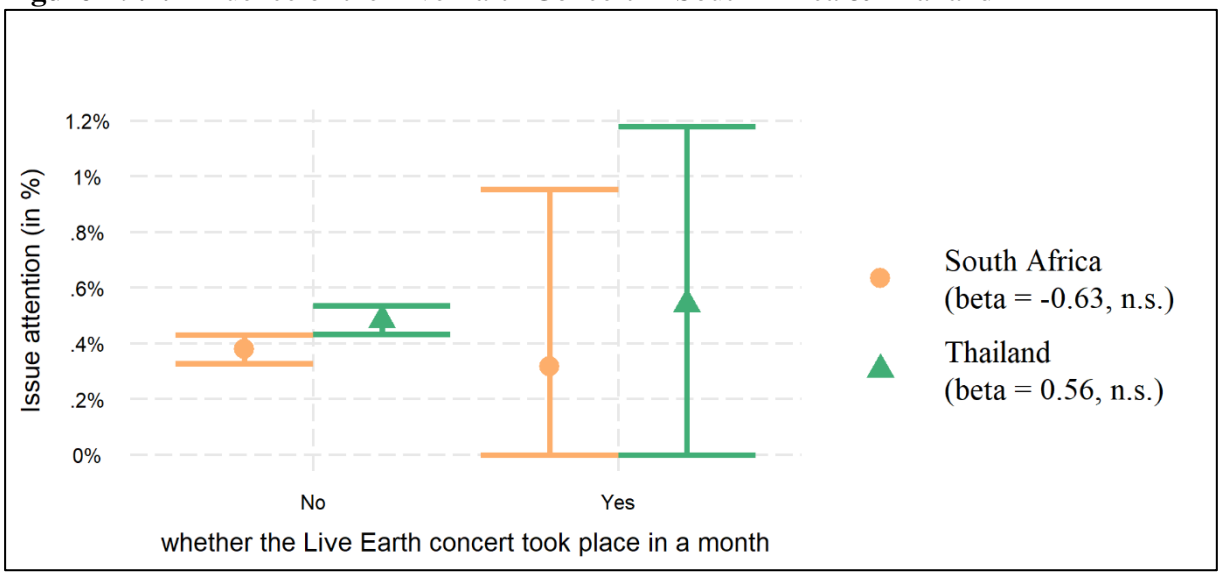
Note: Simple slopes of *Live Earth Concert*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E9.3. Influence of the Live Earth Concert in Namibia & New Zealand



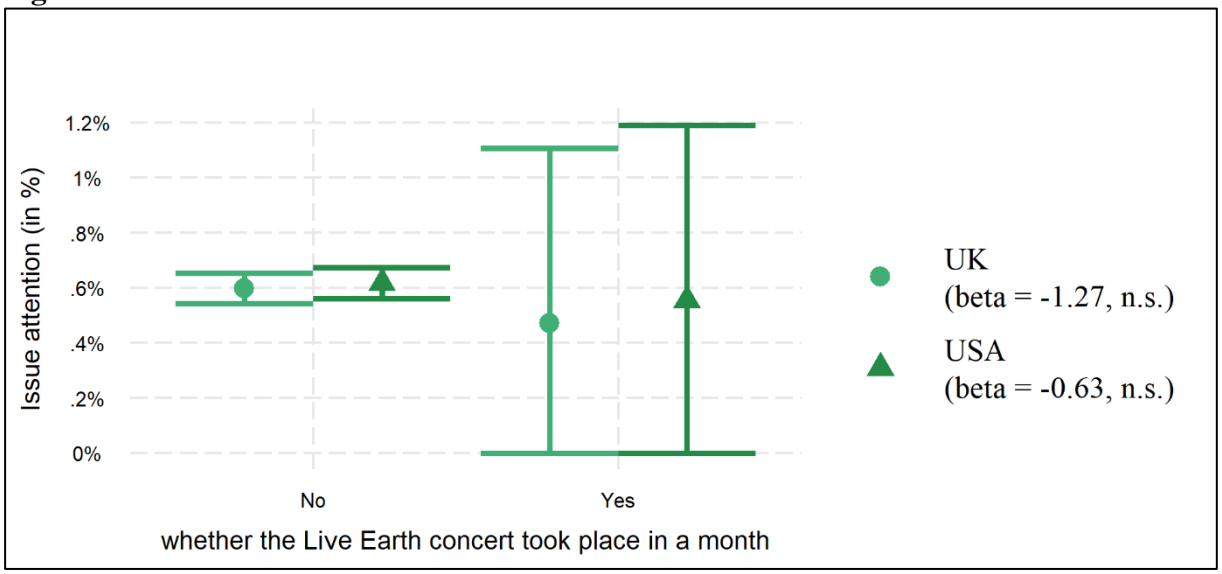
Note: Simple slopes of *Live Earth Concert*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E9.4. Influence of the Live Earth Concert in South Africa & Thailand



Note: Simple slopes of *Live Earth Concert*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E9.5. Influence of the Live Earth Concert in the UK & the US

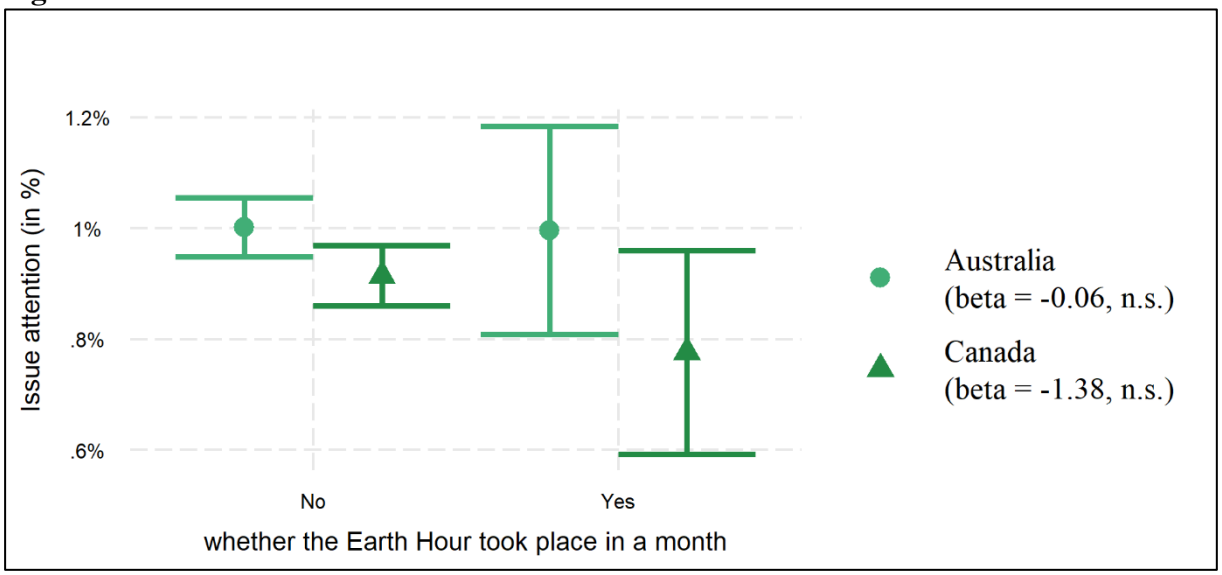


Note: Simple slopes of *Live Earth Concert*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

E10. Influence of Focusing Events across Countries (RQ3): Earth Hour

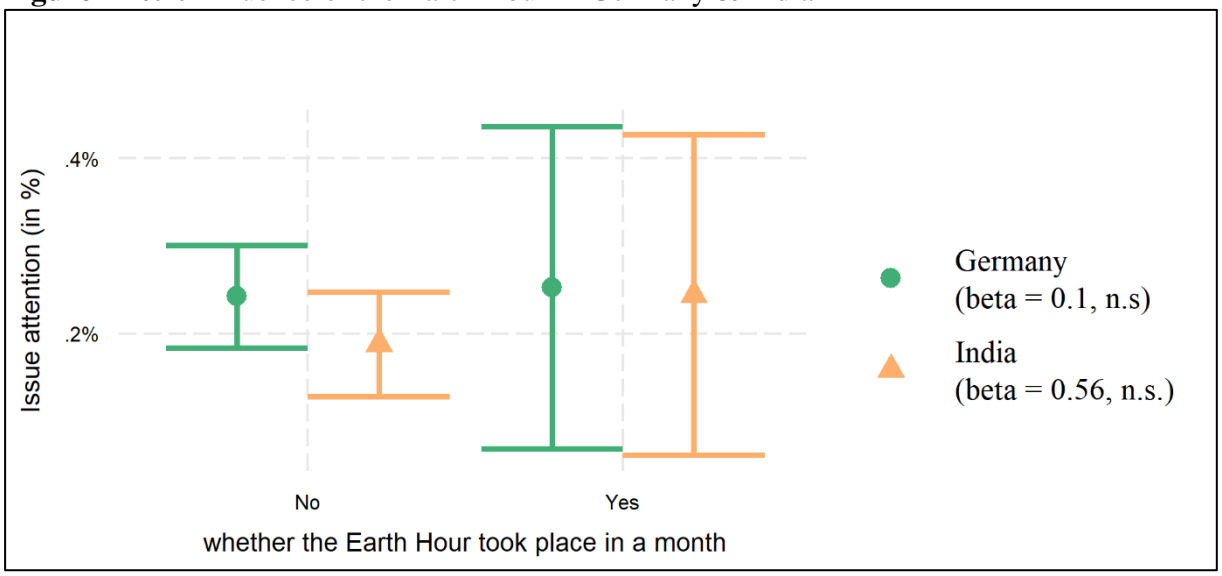
Next, we tested whether the Earth Hour was associated with peaks in issue attention in some countries but not in others. To do so, we included an interaction between country dummies and *Earth Hour*$_t$. **In short, we did not find a consistent effect of the Earth Hour on issue attention in any country.** Figures E10.1–E10.5 visualize the corresponding effects and report the result of each Johnson-Neyman (J-N) test, which indicates whether the simple slope for each country represents a consistent effect or not. If the J-N test is significant, this indicates a consistent effect of the Earth Hour on issue attention within the specific country (p<.05), otherwise there is no consistent effect (n.s.). In all figures, countries from the Global North are depicted in green while countries from the Global South are depicted in orange.

Figure E10.1. Influence of the Earth Hour in Australia & Canada



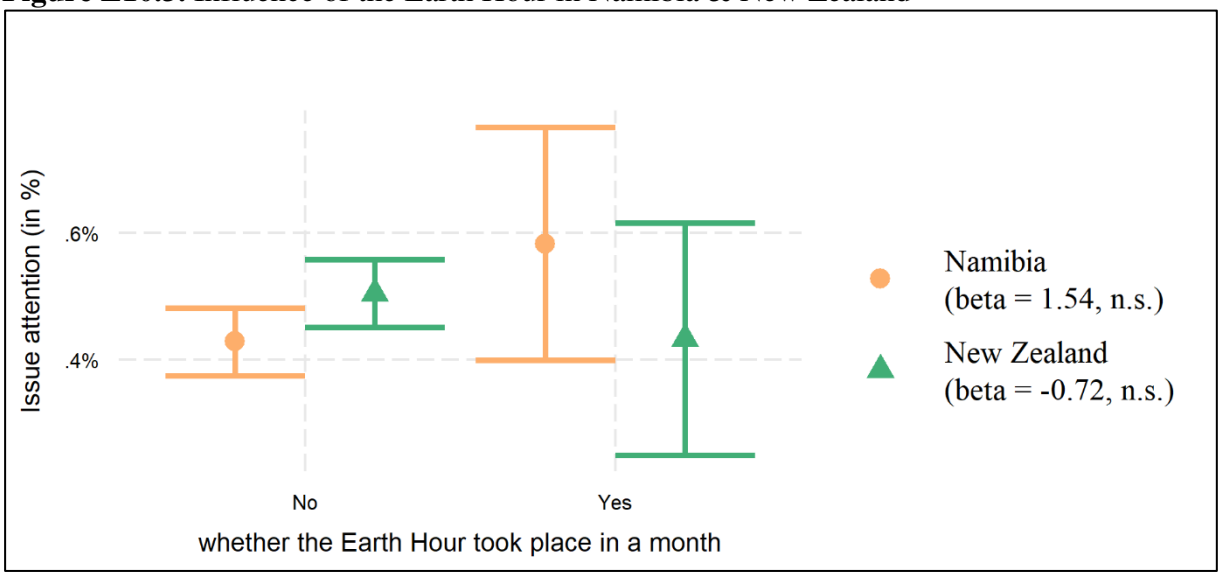
Note: Simple slopes of *Earth Hour*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E10.2. Influence of the Earth Hour in Germany & India



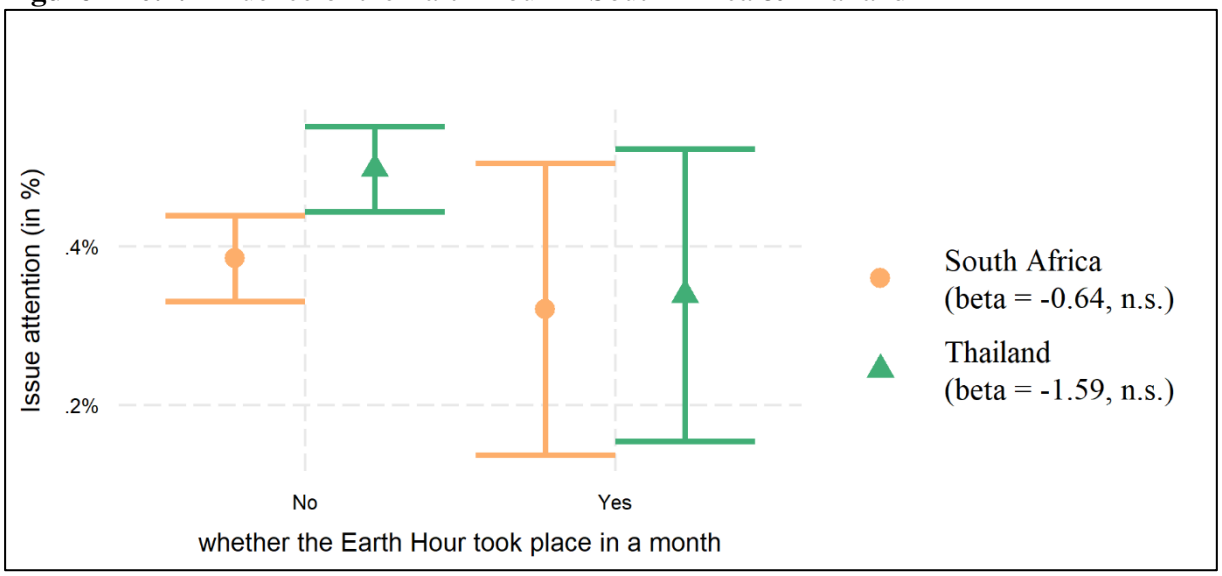
Note: Simple slopes of *Earth Hour*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E10.3. Influence of the Earth Hour in Namibia & New Zealand



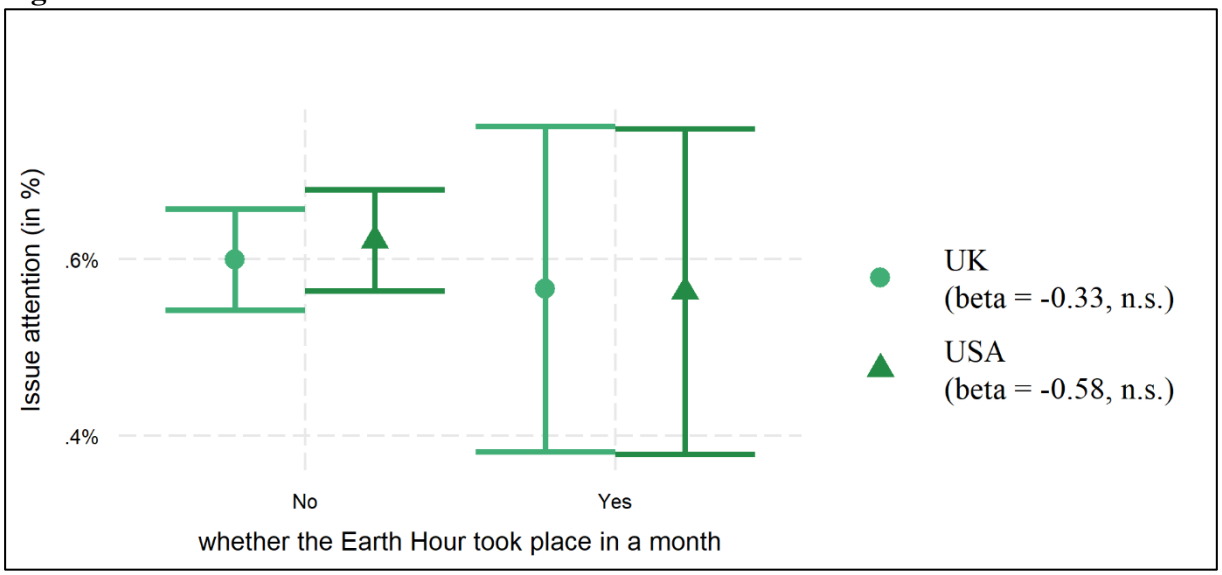
Note: Simple slopes of *Earth Hour*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E10.4. Influence of the Earth Hour in South Africa & Thailand



Note: Simple slopes of *Earth Hour*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E10.5. Influence of the Earth Hour in the UK & the US

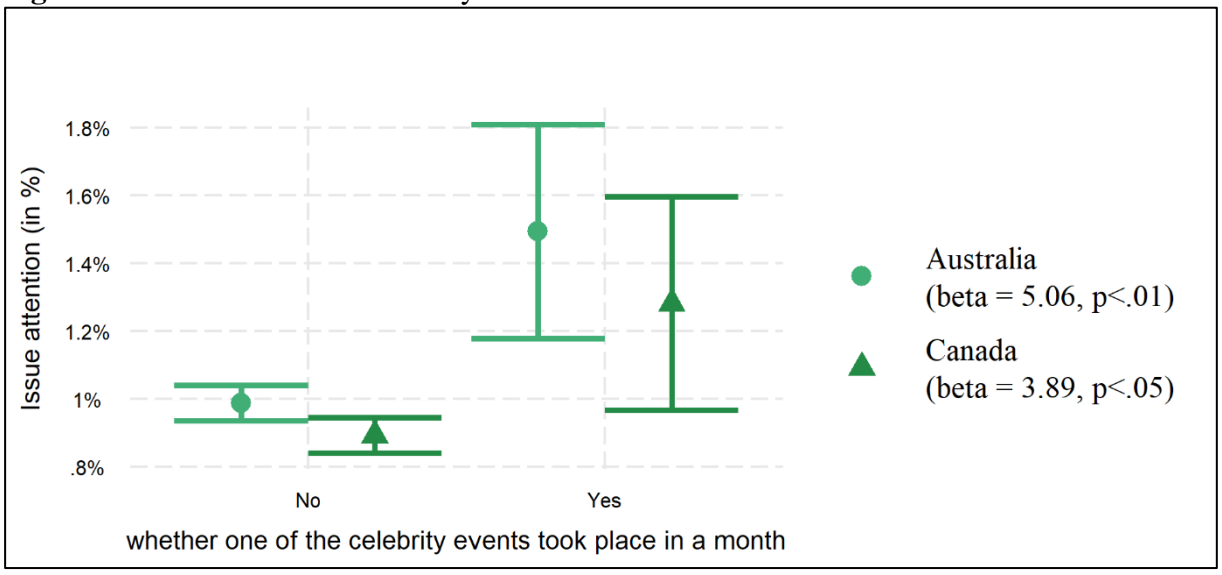


Note: Simple slopes of *Earth Hour*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

E11. Influence of Focusing Events across Countries (RQ3): Celebrity Events

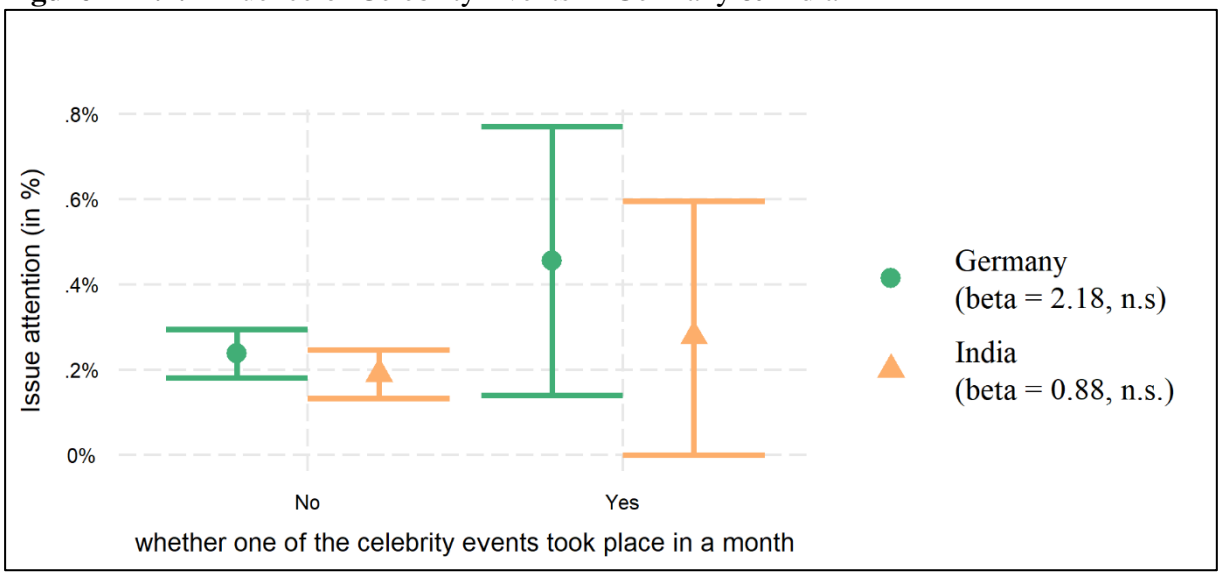
Next, we tested whether events related to celebrity were associated with peaks in issue attention in some countries but not in others. To do so, we included an interaction between country dummies and *Celebrity Events*$_t$. **In short, we found a consistent positive effect of celebrity events on issue attention in Australia and Canada.** Figures E11.1–E11.5 visualize the corresponding effects and report the result of each Johnson-Neyman (J-N) test, which indicates whether the simple slope for each country represents a consistent effect or not. If the J-N test is significant, this indicates a consistent effect of such celebrity events on issue attention within the specific country (p<.05), otherwise there is no consistent effect (n.s.). In all figures, countries from the Global North are depicted in green while countries from the Global South are depicted in orange.

Figure E11.1. Influence of Celebrity Events in Australia & Canada



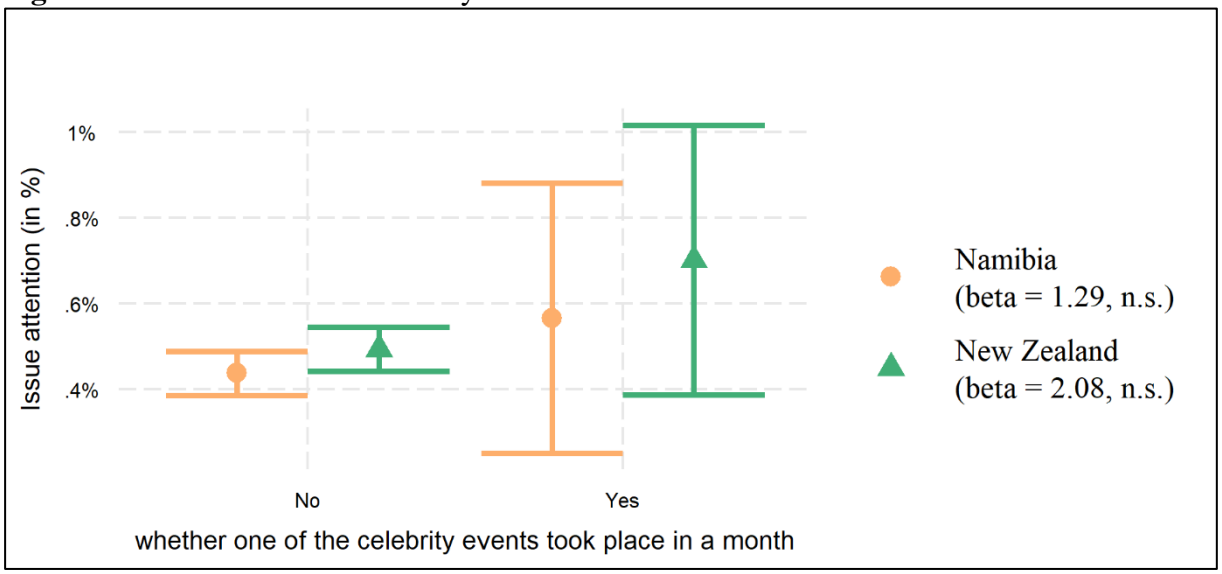
Note: Simple slopes of *Celebrity Events*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E11.2. Influence of Celebrity Events in Germany & India



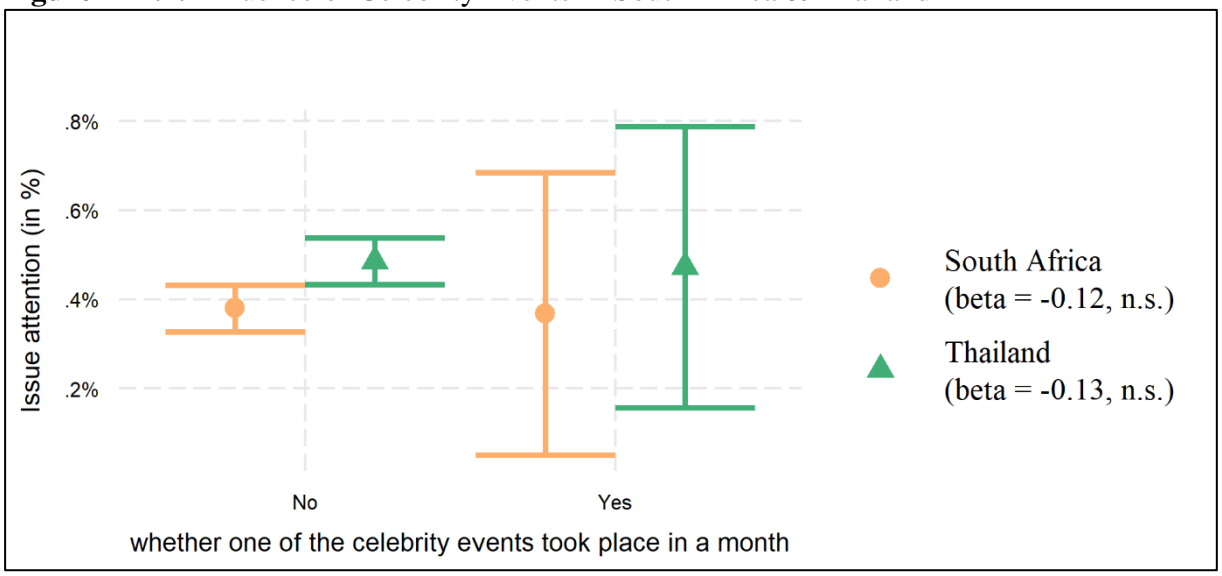
Note: Simple slopes of *Celebrity Events*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E11.3. Influence of Celebrity Events in Namibia & New Zealand



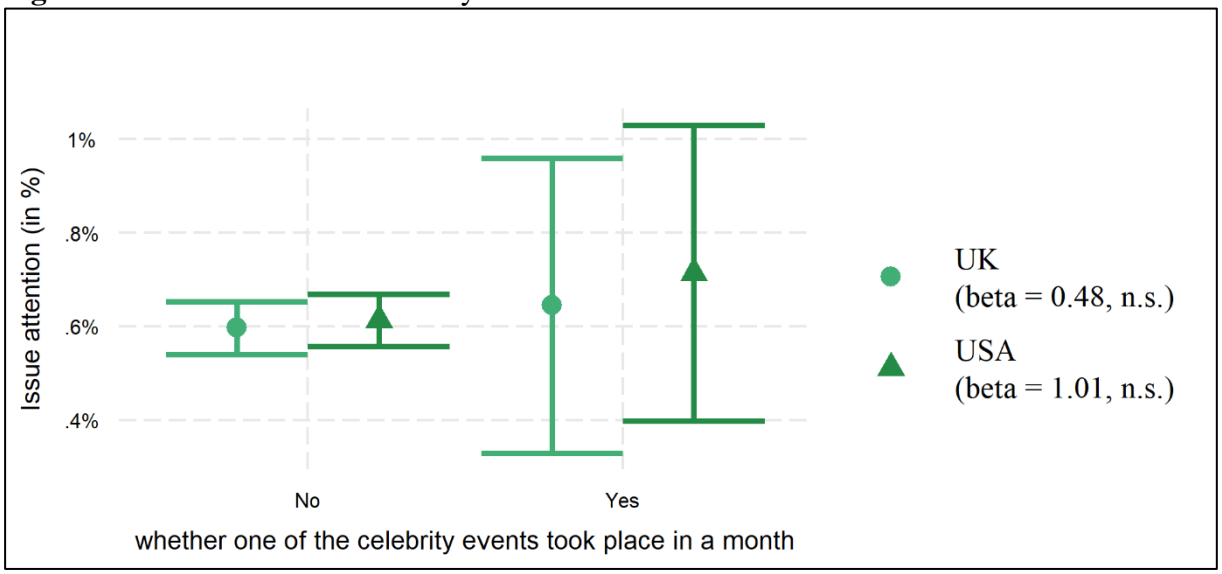
Note: Simple slopes of *Celebrity Events*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E11.4. Influence of Celebrity Events in South Africa & Thailand



Note: Simple slopes of *Celebrity Events*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E11.5. Influence of Celebrity Events in the UK & the US

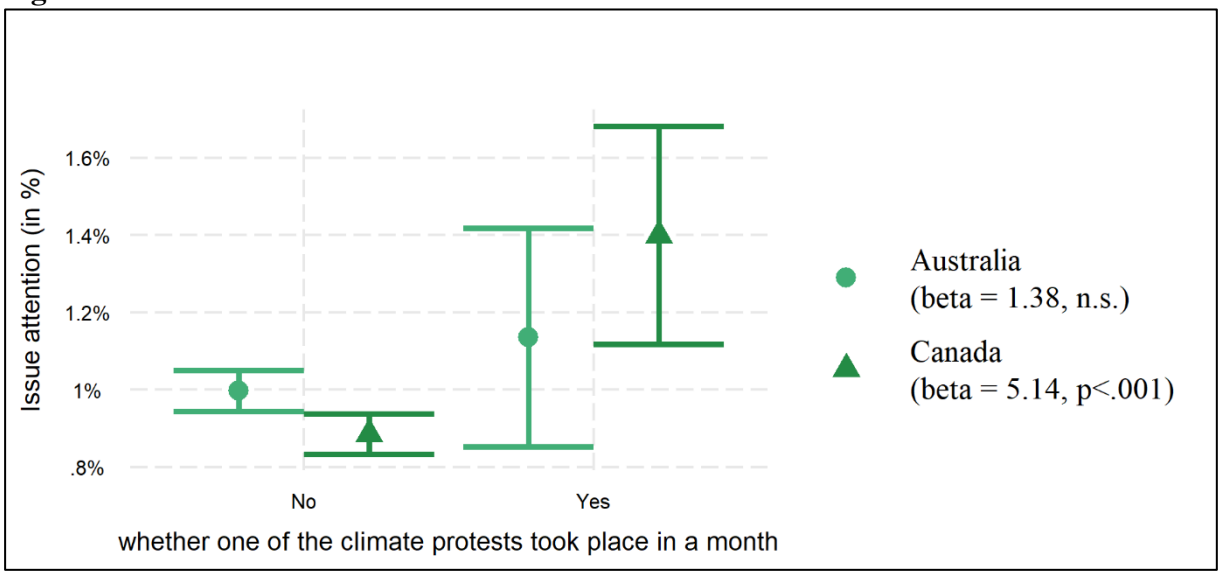


Note: Simple slopes of *Celebrity Events*$_t$ for country$_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

E12. Influence of Focusing Events across Countries (RQ3): Protests

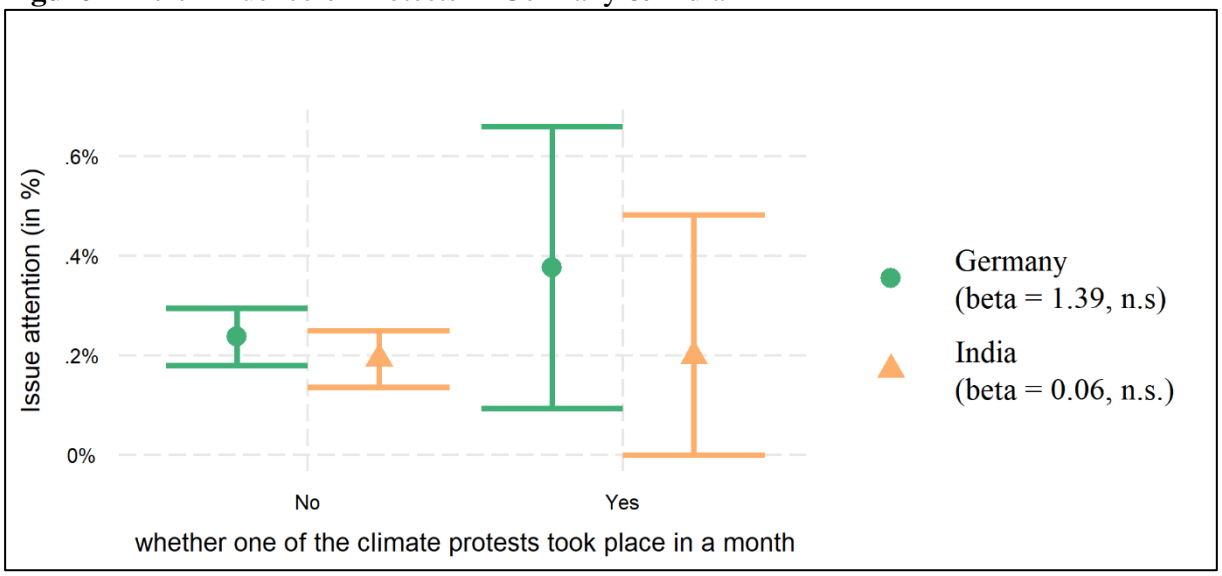
Next, we tested whether climate protests were associated with peaks in issue attention in some countries but not in others. To do so, we included an interaction between country dummies and *Protests*. **In short, we found a consistent positive effect of protests on issue attention in Canada and New Zealand.** Figures E12.1–E12.5 visualize the corresponding effects and report the result of each Johnson-Neyman (J-N) test, which indicates whether the simple slope for each country represents a consistent effect or not. If the J-N test is significant, this indicates a consistent effect of climate protests on issue attention within the specific country (p<.05), otherwise there is no consistent effect (n.s.). In all figures, countries from the Global North are depicted in green while countries from the Global South are depicted in orange.

Figure E12.1. Influence of Protests in Australia & Canada



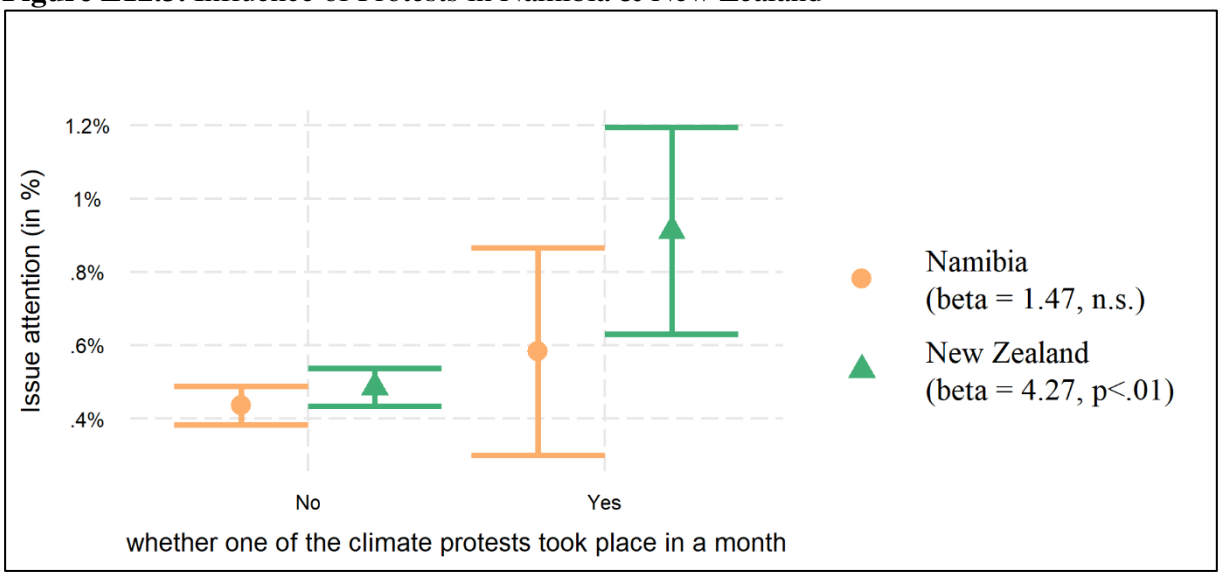
Note: Simple slopes of $Protests_t$ for $country_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E12.2. Influence of Protests in Germany & India



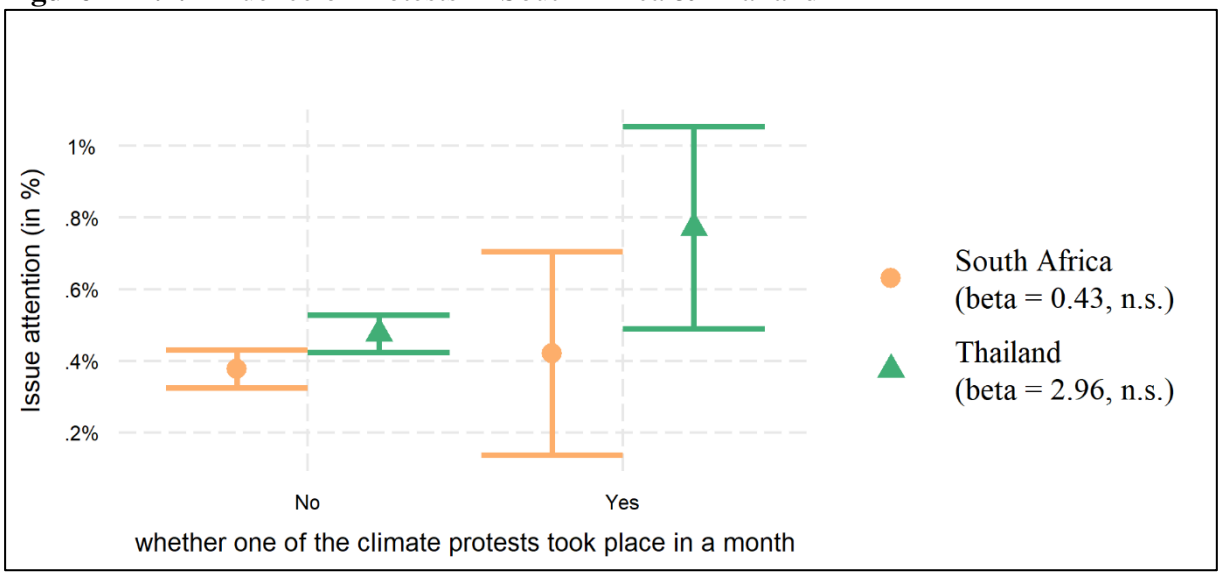
Note: Simple slopes of $Protests_t$ for $country_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E12.3. Influence of Protests in Namibia & New Zealand



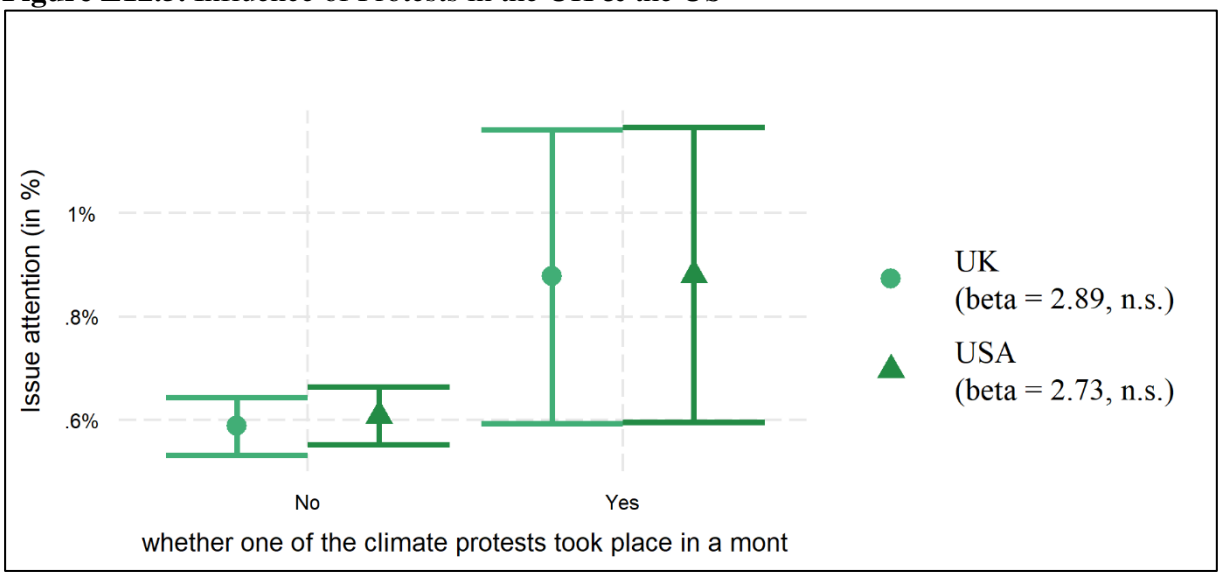
Note: Simple slopes of $Protests_t$ for $country_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E12.4. Influence of Protests in South Africa & Thailand



Note: Simple slopes of $Protests_t$ for $country_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Figure E12.5. Influence of Protests in the UK & the US



Note: Simple slopes of $Protests_t$ for $country_i$ separately. Countries from the Global North are depicted in green, those from the Global South in orange.

Appendix F. Themes and Dimensions Across Countries

Table F1 illustrates the relative share of articles displaying any of the seven themes as their main theme across countries according to our automated content analysis. Table F2 illustrates the same information when comparing countries from the Global North and the Global South, including related significance tests.

Table F1. Prevalence of Themes Across Countries

Country	**% of articles within each country displaying theme (conditional probability of theme in each country)**						
	Climate Change & Impacts on the Ecosystem	Climate Science	Causes of & Solutions to Climate Change	Climate Politics	Awareness & Education	Impacts on Humans	Economic Impacts
Australia	4.16% (.03)	6.72% (.05)	17.92% (.13)	12.67% (.09)	11.07% (.13)	4.16% (.04)	1.66% (.03)
Canada	7.69% (.05)	4.24% (.04)	14.44% (.12)	9.61% (.08)	9.91% (.13)	4.28% (.04)	2.13% (.03)
Germany	9.21% (.08)	5.37% (.05)	6.92% (.1)	6.48% (.08)	3.79% (.09)	4.08% (.06)	1.66% (.03)
India	6.29% (.05)	3.34% (.03)	7.43% (.09)	7.9% (.07)	8.8% (.11)	9.39% (.1)	0.58% (.02)
Namibia	7.19% (.05)	1.96% (.02)	2.94% (.07)	10.13% (.08)	8.5% (.09)	45.1% (.24)	0.33% (.02)
New Zealand	7.34% (.06)	7.77% (.06)	15.66% (.12)	10% (.08)	12.14% (.13)	5.86% (.06)	2.09% (.03)
South Africa	5.94% (.05)	5.5% (.04)	13.13% (.12)	17.61% (.12)	11.81% (.13)	17.98% (.12)	2.71% (.03)
Thailand	5.2% (.04)	3.49% (.03)	13.67% (.12)	15.23% (.1)	11.78% (.13)	12.7% (.11)	3.08% (.04)
UK	8.64% (.06)	7.71% (.06)	16.56% (.12)	11.31% (.09)	11.09% (.13)	6.94% (.06)	3.04% (.03)
USA	8.85% (.06)	7.39% (.06)	12.45% (.11)	16.51% (.11)	8.7% (.11)	5.48% (.05)	2.59% (.03)

Table F2. Prevalence of Themes and Dimensions Between the Global North and South

		% of articles in Global North/South displaying theme (conditional probability of theme)		**Difference in conditional probabilities (according to repeated measures analysis of variance)**
Dimension	Theme	Global North	Global South	Repeated measures ANOVA
Ecological Dimension	*Climate Change & Impacts on the Ecosystem*	7.65% (.05)	6.16% (.05)	$F(1,8) = 0.19$, $p = .67$ (no consistent difference)
Scientific Dimension	*Climate Science*	6.53% (.05)	3.57% (.03)	$F(1,8) = 7.24$, $p < .05$ (consistent difference)
Societal Dimension		41.88% (.41)	55.17% (.43)	$F(1,8) = 0.54$, $p = .49$ (no consistent difference)
	Causes of & Solutions to Climate Change	14% (.12)	9.29% (.1)	$F(1,8) = 4.49$, $p = .07$ (no consistent difference)
	Climate Politics	11.1% (.09)	12.7% (.08)	$F(1,8) = 0.4$, $p = .54$ (no consistent difference)
	Awareness & Education	9.45% (.12)	10.2% (.11)	$F(1,8) = 0.34$, $p = .58$ (no consistent difference)
	Impacts on Humans	5.13% (.05)	21.3% (.11)	$F(1,8) = 29.26$, $p < .001$ (consistent difference)
	Economic Impacts	2.2% (.03)	1.68% (.02)	$F(1,8) = 1.6$, $p = .24$ (no consistent difference)

Note: Last column describes repeated measures analysis of variance (ANOVA) with Bonferroni corrections.

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